

1 **Permanent Relocation Into and Out of Areas Exposed**
2 **to Natural Hazards: a Multidisciplinary Review of the**
3 **Literature**

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Abstract

This article examines the long-term impacts of natural hazards caused by patterns of relocation into and out of hazard-exposed communities. We address two main questions: (1) what factors influence permanent relocation decisions in hazard-exposed communities? (2) What are the effects of relocation on the socio-economic and demographic characteristics of these communities? To answer these questions, we review studies on theoretical frameworks, empirical analyses, and simulation-based models. Relocation outcomes result from a complex interplay of household characteristics (e.g., wealth, risk perception, place attachment), community characteristics (e.g., economic opportunities, essential services), and government interventions (e.g., collective risk-reduction measures). The reviewed studies report mixed findings on demographic and socio-economic changes associated with permanent relocation. Large-scale analyses suggest that natural hazards have limited effects on pre-existing population trends, while more granular studies show that specific hazards—such as coastal flooding and sea level rise—can alter local dynamics. Effects on communities socio-economic characteristics also vary. Some communities experience post-hazard gentrification, while others face deepened vulnerabilities, with declining property values trapping residents in high-risk areas. We further review simulation-based models that examine hazard-related relocation and the socio-economic changes it can produce. These models often focus on specific aspects, such as individual decision-making, housing markets, or recovery patterns, without integrating all relevant factors. Finally, we identify key research gaps, including the need for more long-term studies on socio-economic changes in hazard-exposed communities, and greater focus on chronic, low-intensity hazards like tidal flooding.

1 Introduction

Residents of hazard-exposed areas typically respond to natural hazards in one of two ways: they either remain in place adapting to the risk, or relocate elsewhere. The decision to stay or to leave depends on a combination of aspirations (what they prefer) and capabilities (what they can afford) (de Haas, 2021). Figure 1 illustrates different ways in which responses to natural hazards can unfold. For example, residents of exposed areas may act individually by taking measures to reduce the vulnerability of their homes, or collectively by implementing community-wide initiatives, such as early warning systems. Likewise, relocation can be unmanaged, where individual households independently decide whether to leave, or managed, with government-led programs coordinating relocation efforts (e.g., neighborhood buyouts) (Weber & Moore, 2019).

In the context of hazard-induced relocation, it is important to distinguish between temporary and permanent relocation. According to Paul et al. (2024), natural hazards can trigger both evacuation and displacement, two forms of temporary relocation. Evacuation is typically a preemptive measure in which individuals leave the exposed area before or during the hazard. Displacement, on the other hand, involves longer durations and affects those whose homes or neighborhoods have been damaged, preventing an immediate return. The duration of displacement can range from a few days to several years, depending on the time needed to repair buildings, restore infrastructure, and reestablish essential services. Permanent relocation often takes place during the recovery period. For example, some displaced residents return to their homes, while others relocate elsewhere with the intent to remain long-term. At the same time, residents who were not displaced may also choose to leave, for instance due to concerns about future hazards. New residents, who were not living in the community before the hazard, may also move in. This population reshuffling, driven by permanent in- and out-relocation, can lead to significant socio-economic and demographic changes, including population growth or decline, gentrification, or increased impoverishment. This literature review focuses on unmanaged, permanent relocation, defined as residents' long-term movement into or out



ADAPTATION					
		INDIVIDUAL LEVEL 		COMMUNITY LEVEL 	
		Infrastructure Measures	Non-Infrastructure Measures	Infrastructure Measures	Non-Infrastructure Measures
IN-PLACE		Home elevation Dry floodproofing Wet floodproofing Backup valve	Insurance	Seawalls and Levees Drainage infrastructure upgrade Street elevation	Transfer of Development Rights (TDR) Hazard prediction and Mapping Hazard monitoring and Early warnings
	RELOCATION	Individual relocation		Managed relocation (e.g., buyouts)	

Figure 1. Common adaptation strategies for disaster risk management. Adaptation strategies are categorized by scale (individual-level and community-level) and type (infrastructural and non-infrastructural), with distinctions between in-place measures and relocation strategies. For illustrative purposes, the infrastructure adaptation measures listed here refer specifically to flooding, while this classification applies to any type of natural hazard. Created in BioRender. Malakun, A. (2025) <https://BioRender.com/1z4sd7q>

65 of hazard-exposed areas, without government coordination, and the socio-economic and
66 demographic changes it produces in affected communities.

67 In this paper, we address two main questions using existing literature. The first
68 question is the following: what are the factors that, together with natural hazards, in-
69 fluence patterns of relocation into and out of hazard-exposed communities? According
70 to the reviewed literature, permanent relocation patterns are driven by several factors,
71 including economic trends, political stability, social networks, environmental hazards, and
72 resilience levels at both the origin and destination (Black et al., 2011). These drivers of-
73 ten interact and influence one another. As a result, relocation outcomes may vary sig-
74 nificantly across individuals and communities, even when they are exposed to the same
75 hazard. Our second question is what socio-economic and demographic changes can be
76 caused by hazard-induced relocation. Both in- and out-relocation can result in signif-
77 icant changes within a community (van Holm & Wyczalkowski, 2019). For example, if
78 the rate of permanent out-relocation exceeds in-relocation, the total population may re-
79 duce. Even if population size remains stable, differences in the characteristics of out-movers,
80 remaining residents, and newcomers can alter the community’s composition. For instance,
81 if over time most out-movers are low-income and most newcomers are high-income, the
82 community will become on average more affluent (Graff Zivin et al., 2023). In address-
83 ing these questions, we focused primarily on communities in developed economies. As
84 explained in the following section, responses to natural hazards differ fundamentally be-
85 tween developed and developing economies, and covering both would have made our re-
86 view excessively broad.

87 To answer our questions, we review studies on hazard-induced relocation from var-
88 ious disciplines, including sociology, economics, urban planning, geography, and engineer-
89 ing. Existing reviews have examined hazard-induced newcomers from specific disciplinary
90 perspectives, providing a fragmented description of the phenomenon. For example, sev-
91 eral authors have reviewed studies from the sociological subfield of environmental mi-
92 gration, which investigates migration outcomes in relation to environmental factors. These
93 reviews consider a broad range of environmental factors, including catastrophic events,
94 rising temperatures, and changing precipitation patterns. Reviews from this field focus
95 on three main areas. First, some reviews examined theoretical frameworks from the broader
96 field of migration studies and applied them to environmental migration research (de Sherbinin
97 et al., 2022; Hunter et al., 2015; Piguët, 2018). They use frameworks such as the push
98 and pull theory (Wolpert, 1966; Speare, 1974) and the new economics of labor migra-
99 tion (Stark & Bloom, 1985) to explain migration patterns driven by environmental fac-
100 tors. A second group of authors reviewed empirical evidence on how environmental fac-
101 tors influence migration (Almulhim et al., 2024; Daoust & Selby, 2024; Hoffmann et al.,
102 2020; Kaczan & Orgill-Meyer, 2020; Millock, 2015). They summarized findings from stud-
103 ies that use data analysis or surveys to assess the effects of environmental factors on mi-
104 gration. Lastly, some reviews focused on the empirical methods most commonly used
105 in environmental migration studies, such as spatial statistical analyses and survey-based
106 approaches (Cipollina et al., 2024; Piguët, 2022). Most studies in the environmental mi-
107 gration literature focus on agriculture-dependent communities in developing economies.
108 Moreover, they primarily examine how environmental factors can force out-migration (or
109 immobility, as explained in the following section), without considering the long-term con-
110 sequences of both in- and out-migration on exposed communities.

111 A separate body of reviews examined the effects of sea level rise (SLR) on reloca-
112 tion outcomes. For example, Duijndam et al. (2022) and Hauer et al. (2020) investigated
113 the various ways SLR is prompting permanent out-relocation from exposed regions. They
114 analyzed the effects of SLR on developed economies, developing economies, and atoll is-
115 lands, highlighting their different responses to the hazard. These reviews focus exclu-
116 sively on one type of natural hazard—SLR—and its influence on permanent out-relocation
117 from exposed locations. Adopting a different perspective, Greer et al. (2019) and Paul

118 et al. (2024) reviewed studies on household-level decisions to permanently relocate out
119 of hazard-exposed communities. Their reviews provide a comprehensive overview of fac-
120 tors influencing permanent relocation outcomes, including place attachment, the extent
121 of hazard-induced damage, and risk perception. Both reviews offer valuable insights on
122 factors that influence permanent relocation out of exposed areas. However, they do not
123 address relocation of new residents into hazard-affected areas or the demographic and
124 socio-economic consequences of relocation patterns on hazard-exposed communities. Lastly,
125 Noy and Iv (2018) and Arcaya et al. (2020) reviewed studies on the long-term consequences
126 of catastrophic natural hazards, each with a distinct focus. Noy and Iv (2018) examined
127 economic impacts, including effects on income, productivity, health, education, and de-
128 mographic trends, framing all observed changes through an economic lens. Arcaya et al.
129 (2020) reviewed the sociological literature, highlighting key conceptual distinctions within
130 the field. For example, they emphasized the importance of differentiating between individual-
131 and community-level recovery, and between short-term and long-term dynamics. Both
132 reviews acknowledge relocation patterns as a factor shaping long-term post-hazard out-
133 comes, but neither focuses specifically on hazard-induced relocation.

134 While each of these reviews examines hazard-induced relocation and its effects from
135 a distinct perspective, our work complements these studies by adopting a broader point
136 of view. Our approach considers multiple types of hazards, examines relocation both into
137 and out of hazard-affected communities, and investigates the long-term effects of these
138 relocation patterns on the affected communities. To identify relevant works, we employed
139 a snowball sampling approach (Wohlin, 2014), expanding the pool through references
140 in each reviewed study that addressed our two research questions. We reviewed 141 works,
141 including 125 scientific papers, 6 technical reports, 1 dissertation, 4 book chapters, and
142 5 news articles. Among the scientific papers, most analyze empirical data, either from
143 publicly available sources (e.g., property sales data) or from surveys conducted specifi-
144 cally for the study. Some articles present theoretical frameworks that help interpret em-
145 pirical findings, while others develop mathematical models and use computer simulations
146 to explain underlying mechanisms. To guide the reader through this comprehensive lit-
147 erature review, Figure 2 outlines its main sections and illustrates how they are intercon-
148 nected. First, we provide an overview of the field of environmental migration, contex-
149 tualizing the role of environmental stressors within the broader scope of migration stud-
150 ies. This section highlights how multiple factors influence hazard-induced migration and
151 how communities with different characteristics can experience varying migration outcomes
152 even when exposed to the same hazard. Building on these insights, the following two sec-
153 tions examine the factors that interact with natural hazards in shaping relocation pat-
154 terns, and the varying long-term effects of hazard-induced relocation across communi-
155 ties with different characteristics. The final section focuses on existing mathematical mod-
156 els that simulate interactions between natural hazards, the built environment, and hu-
157 man communities. For each model, we assess the influencing factors considered and the
158 long-term effects they reproduce, highlighting potential combinations of different mod-
159 els to obtain more comprehensive results. Finally, we summarize the key findings from
160 the reviewed literature, identify major knowledge gaps, and suggest areas for future re-
161 search.

162 **2 Environmental Migration**

163 To investigate relocation patterns in areas exposed to natural hazards, we began
164 by reviewing the literature on environmental migration. Environmental migration research
165 examines how environmental factors—such as natural hazards, climate change, and ecosys-
166 tem shifts—affect long-term migration of human communities. It draws on theoretical
167 frameworks from the broader field of migration studies (e.g., push and pull theory, new
168 economics of labor migration) to interpret migration outcomes in relation to environmen-
169 tal drivers (de Sherbinin et al., 2022; Piguet, 2018). Daoust and Selby (2024) and Gutmann

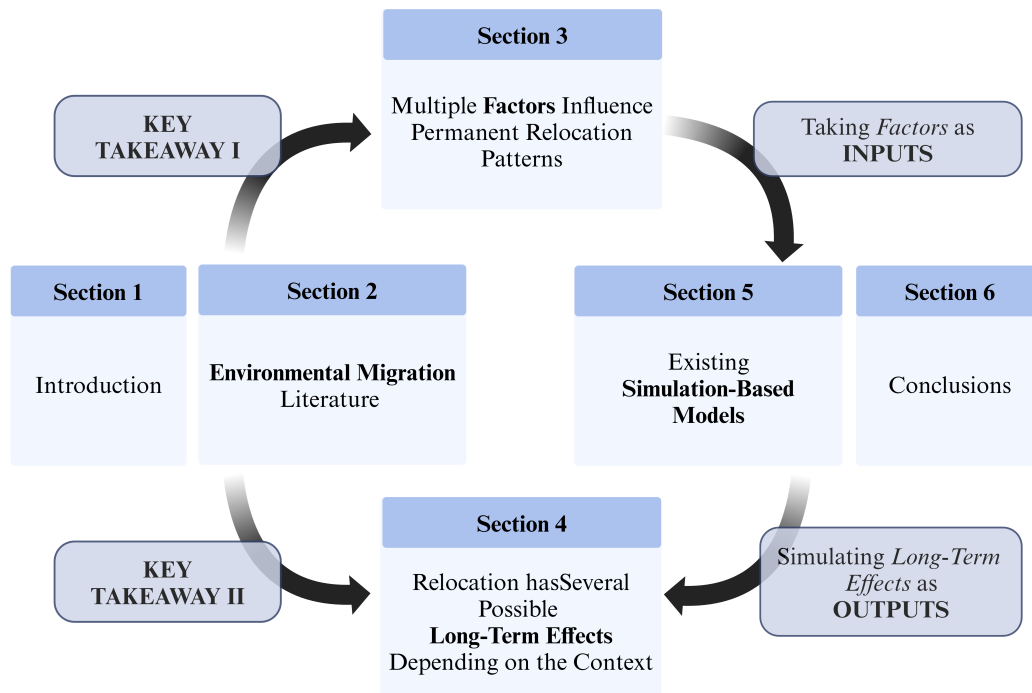


Figure 2. Outline of this literature review. Research on environmental migration (Section 2) highlights two key points: relocation patterns are influenced by multiple interconnected factors, including natural hazards (Section 3), and these factors have varying effects depending on the specific context (Section 4). Several simulation-based models integrate these factors to capture their diverse effects (Section 5). Created in BioRender. Malakun, A. (2025) <https://BioRender.com/1z4sd7q>

170 and Field (2010) classified environmental drivers into four categories: environmental calamities
171 (sudden, destructive hazards like cyclones and tornadoes), environmental hardships
172 and benefits (slow-onset phenomena such as droughts and tidal flooding, as well as temporary
173 climatic variations favorable to agriculture), environmental amenities (such as favorable
174 weather or proximity to water and mountains), and environmental barriers and
175 their management (technology and infrastructure that help humans adapt to unfavorable
176 environments, such as air conditioning, flood control, and irrigation systems). In
177 this review, we primarily investigate the effects on migration of environmental calamities
178 and hardships, here referred to as natural hazards¹. However, as it will become evident
179 in the following sections, all four categories are interconnected and must be considered
180 together.

181 The main takeaway from the field of environmental migration is that environmental
182 drivers influence migration in conjunction with other factors (Black et al., 2011; Hoffmann
183 et al., 2020; Hunter et al., 2015). For example, Black et al. (2011) differentiates
184 between macro-scale factors, such as macroeconomic and environmental conditions, and
185 micro-scale factors, such as a household's financial capacity. These drivers—they explain—
186 interact among each other in shaping migration outcomes. For instance, natural hazards
187 may force a large factory to permanently shut down, reducing employment opportunities
188 and prompting out-migration. The fact that migration results from multiple, inter-
189 connected factors has an important implication: the effects of natural hazards on migration
190 are highly context-dependent. Communities with different socio-economic, environ-
191 mental, and institutional characteristics can experience vastly different migration out-
192 comes, even when exposed to the same environmental drivers. For example, Chen and
193 Rosenthal (2008) and Graves (1979) investigated the relative influence of different mi-
194 gration drivers across demographic groups in the US. They found that younger individ-
195 uals primarily migrate for economic opportunities, while older populations are more drawn
196 to natural amenities. Moreover, several studies have shown that natural hazards have
197 a stronger impact on agriculture-dependent communities, as damage to agriculture di-
198 rectly affects their local economies (Bohra-Mishra et al., 2014; Cipollina et al., 2024; Dragomir,
199 2021; Piguet, 2022). For example, Dragomir (2021) examined how slow-onset environ-
200 mental changes disrupt agriculture-based livelihoods in South India, driving out-migration
201 in search of alternative economic opportunities. This effect is particularly pronounced
202 in developing economies, where subsistence farming is common, compared to market economies
203 where widespread insurance may mitigate risks. Research on internal migration in the
204 US supports this contrast between developed and developing economies: in the early 20th
205 century, when subsistence agriculture was widespread, environmental hardships were a
206 major driver of out-migration. However, as the economy developed and populations be-
207 came more affluent, environmental hardships had little influence on migration, while en-
208 vironmental amenities began attracting residents to high-amenity areas (Gutmann & Field,
209 2010). Given these differences in responses to natural hazards between developed and
210 developing economies, we chose to focus our review on the former. Therefore, most of
211 the studies examined in the following sections are based on developed economies, such
212 as the contemporary US.

213 Another key takeaway from the environmental migration literature, further illus-
214 trating how environmental migration is context-dependent, is that natural hazards can
215 simultaneously drive out-migration and cause immobility. Schewel (2020) and Zickgraf
216 (2021) frame this duality through different theoretical frameworks, including the aspirations-
217 capabilities framework (de Haas, 2021). According to this framework, natural hazards,
218 in conjunction with other factors, can shape both the aspiration to out-migrate and the

¹ In this review, we adopt a broader perspective on natural hazards, including geophysical events such as earthquakes and tsunamis, which, while not classified as environmental hazards in strict scientific terms, pose similar risks to human communities as events like flooding and tornadoes.

219 capability to do so, potentially leading to either forced migration or forced immobility.
220 For example, a homeowner in a high-demand neighborhood may lack the resources to
221 rebuild after a flood, but still be able to sell their property at a high price and relocate
222 to a more affordable area. Even if they would have preferred to stay put, out-migration
223 becomes their most practical choice—a form of forced migration (Piguet, 2018). Con-
224 versely, a resident in a low-value housing market may experience severe flood damage
225 that depletes their savings, while their property is not valuable enough to finance relo-
226 cation. In such cases, despite wanting to leave, financial barriers prevent out-migration,
227 a situation commonly described as poverty trap. Empirical findings confirm the dual out-
228 come of forced migration or immobility for similar levels of exposure to natural hazards.
229 For example, Letta et al. (2024) analyzed household-level responses to environmental stres-
230 sors in Nigeria, finding that households with greater resources are more likely to out-migrate.
231 However, the relationship between wealth and out-migration is not always the same. As
232 discussed in the following section, wealthier households may also be more likely to stay,
233 as they have better financial means to face hazard-related damages.

234 In summary, two key insights emerge from the environmental migration literature.
235 First, migration in hazard-exposed communities is shaped by a complex interplay of fac-
236 tors, with natural hazards being just one of them. Second, this interplay makes migra-
237 tion outcomes highly context-dependent, varying across communities with different socio-
238 economic, environmental, and institutional characteristics. The common assumption that
239 exposure to natural hazards inevitably leads to permanent out-migration oversimplifies
240 this complexity. In the following sections, we first analyze the most relevant factors that,
241 in conjunction with natural hazards, can influence permanent relocation. We then ex-
242 amine what are the long-term effects of hazard-induced relocation in communities with
243 varying characteristics, focusing on changes in population size and socio-economic com-
244 position.

245 **3 Factors Influencing Relocation Patterns in Hazard-Exposed Com-** 246 **unities**

247 Natural hazards interact with several other factors to shape relocation patterns.
248 We classified these factors into four main categories (Table 1). First, different types of
249 natural hazards influence relocation in different ways, depending on their characteris-
250 tics, such as their intensity and frequency. Second, relocation patterns depend on household-
251 level characteristics, such as risk perceptions, and community-level characteristics, such
252 as macro-economic conditions. Lastly, policies and government intervention can also in-
253 fluence relocation outcomes in conjunction with natural hazards.

254 **3.1 Hazard Characteristics**

255 ***3.1.1 Hazard Frequency and Intensity***

256 Natural hazards vary in their characteristics, leading to different relocation out-
257 comes. The first distinction that emerges from the literature is between high-intensity,
258 rare events and low-intensity, high-frequency ones. Examples of high-intensity, rare events
259 are earthquakes, storm surges, and tornadoes, while examples of low-intensity, chronic
260 hazards are tidal flooding and seasonal heatwaves. This distinction is especially relevant
261 for coastal flooding, where some communities may only face intense but rare storm surges,
262 while others additionally experience frequent, lower-intensity tidal flooding. Tidal flood-
263 ing is a type of coastal flooding driven by elevated sea levels due to offshore winds and
264 lunar effects (Gold et al., 2023). As sea levels rise, they can directly submerge parts of
265 urbanized land or indirectly prevent stormwater drainage systems from discharging rain-
266 water into the sea, leading to the accumulation of rainwater on land. This form of flood-
267 ing results in frequent, persistent flood events affecting low-lying coastal areas. Tidal flood-
268 ing is usually less intense than storm surges, and its frequent occurrence often prompts

Hazard Characteristics	Household Characteristics	Community Characteristics	Policies and Government
Hazard frequency and intensity	Physical damages and financial capacity	Essential services and infrastructure	In-place adaptation measures
Availability and feasibility of in-place risk reduction measures	Place attachment and social networks	Job opportunities	Buyouts
Hazard spatial predictability	Risk perception	Anchors of social networks	Post-Hazard Economic Assistance
	Housing tenure and housing type	Natural characteristics	
	Demographic characteristics		

Table 1. Factors influencing permanent relocation into and out of hazard-exposed communities.

communities to undertake in-place adaptation measures. However, tidal flooding can still cause severe disruptions that might prompt relocation, as illustrated in The Washington Post report on Carolina Beach, a coastal town in North Carolina, US (Dennis et al., 2024). The article reports that one of the town’s main roads experienced flooding 60 times over the past year, making some residents unable to leave their homes for several hours at a time. Tidal flooding is closely linked to SLR, which increases the frequency of flooding events. Over time, rising sea levels can intensify tidal flooding to the extent that some areas of land may become uninhabitable. L. Perch-Nielsen et al. (2008) compared the impacts of rare, severe flooding with those induced by SLR and tidal flooding. In their review of case studies, they explored the direct and indirect effects of these hazards, along with available adaptation strategies (among which out-relocation is one of the options). They conclude that tidal flooding due to SLR, through progressive land loss, is more likely to drive long-term out-relocation than intense but infrequent flood events.

3.1.2 Availability and Feasibility of In-Place Risk Reduction Measures

The specific characteristics of natural hazards also determine the type and feasibility of adaptation measures needed to reduce risk. Some hazards allow for relatively inexpensive risk-reduction measures, while others require costly and prolonged interventions that may be unaffordable for many households. Aerts (2018) provides a review of in-place risk-reduction measures for flooding. As shown in Table 2, house-level risk-reduction costs can vary widely, from a few thousand to several hundred thousand US dollars. Areas exposed to different types or intensities of flooding may require distinct risk-reduction strategies, resulting in varying financial burdens for homeowners. For instance, a building at risk of sewer backup due to heavy rainfall can be protected by installing a back-flow prevention valve in the sanitary piping (Sandink & Binns, 2021), a relatively low-cost intervention. In contrast, a house in a floodplain may need to be elevated to meet building code requirements, a complex and expensive process (Aerts, 2018). Beyond direct costs, the complexity of different adaptation measures also varies. Some measures can be completed while occupants remain in their homes or require only short-term displacement (e.g., days or a few weeks), while others necessitate prolonged relocation (e.g., up to a few months), adding the financial and emotional burden of securing temporary

299 housing. The costs, complexity, and duration of risk-reduction works can make in-place
300 adaptation unaffordable for some households, increasing the likelihood of out-relocation.

301 *3.1.3 Hazard Spatial Predictability*

302 Another hazard characteristic affecting long-term impacts on relocation patterns
303 is spatial predictability. For instance, storm surge flooding in the US is typically expected
304 in coastal regions prone to hurricanes, such as the Atlantic and Gulf coasts. Tornadoes,
305 on the other hand, are common in the so-called Tornado Alley. Within these large ar-
306 eas, spatial boundaries of storm surge flooding can be predicted relatively accurately, as
307 they depend on well-known factors like topography. Conversely, the spatial occurrence
308 of tornadoes within the Tornado Alley is far less predictable. Thus, some hazards are
309 more spatially predictable than others. The relevance of spatial predictability for relo-
310 cation patterns is identified in a study by Indaco and Ortega (2024). In their analysis,
311 they compared US Census tracts within commuting zones and found that tracts with
312 a high frequency of coastal flooding experienced considerably less population growth than
313 neighboring tracts. When applying the same analysis to other types of hazards, they did
314 not observe this trend. The authors suggest that residents in areas with spatially pre-
315 dictable hazards, like coastal flooding, can opt to live in safer locations while still enjoy-
316 ing the region’s broader appeal. In contrast, in regions exposed to less spatially-predictable
317 hazards, such as tornadoes, identifying safer areas within a commuting zone is not pos-
318 sible. Interestingly, this reduced population growth was only observed in regions exposed
319 to coastal flooding, but not to fluvial flooding. One possible explanation is that coastal
320 areas, in general, attract more residents than inland areas (Neumann et al., 2015). As
321 a result, differences in population growth rates between high-risk and low-risk tracts may
322 be more noticeable in coastal regions, where overall population growth tends to be higher.
323 The study by Boustan et al. (2020) further confirmed that different types of hazards af-
324 fect relocation patterns in different ways. By analyzing net relocation patterns in US coun-
325 ties from 1980 to 2010, the authors found that severe floods are linked to higher out-relocation,
326 while severe tornadoes show no significant impact on relocation patterns.

327 **3.2 Household-level Characteristics**

328 Household-level characteristics play an important role in shaping relocation out-
329 comes following a natural hazard. For example, some residents may be forced to leave
330 due to financial constraints or extensive damage, while others may remain due to strong
331 community ties or limited relocation options. The literature reviews by Greer et al. (2019)
332 and Paul et al. (2024) examine the characteristics of residents in hazard-exposed com-
333 munities that shape out-relocation outcomes. Here, we build on their findings by incor-
334 porating insights from additional studies.

335 *3.2.1 Physical Damage and Financial Capacity*

336 According to both Greer et al. (2019) and Paul et al. (2024), one of the primary
337 factors influencing out-relocation after a destructive natural hazard is the extent of phys-
338 ical damage experienced by the individual households. Generally, households that suf-
339 fer greater damage are more likely to permanently relocate (Bukvic et al., 2015; Mayer
340 et al., 2020). Paul et al. (2024) explained that severe damage often leads to longer re-
341 covery times, extending the period of dislocation, which increases the likelihood of per-
342 manent relocation. Additionally, higher levels of damage require substantial economic
343 resources for repairs or reconstruction. Greer et al. (2019) emphasized that the relation-
344 ship between damage and out-relocation is closely tied to a household’s financial capac-
345 ity, including access to insurance, external aid, private credit, and personal savings. For
346 example, Nejat and Ghosh (2016) surveyed residents heavily affected by Hurricane Sandy
347 and found that access to home insurance and financial assistance from government and

Table 2. Summary of house-level, structural flood adaptation measures from Aerts (2018). Cost estimates are primarily derived from case studies in the US, UK, and Germany, converted to 2016 US dollars using inflation-adjusted consumer price indices. The reported cost ranges represent the minimum and maximum values found in the literature, reflecting variations due to building type, material costs, labor rates, and regulatory requirements. Duration and necessity to vacate during works are not directly reported in the article, but are inferred based on the description of the necessary works and on the engineering judgment of the authors.

Adaptation Measure (1)	Description of Works (2)	Cost (USD, 2016) (3)	Duration (4)	Need to Vacate (5)
Elevation (Average Building)	Lifting the structure above flood level, modifying the foundation, adjusting plumbing/electrical systems.	\$19,481–194,496 per building (US)	Weeks to months, depending on elevation height and complexity.	Yes (home is lifted, utilities are disconnected).
Dry Flood-Proofing (+0.6m)	Sealing walls, installing waterproof coatings, using removable flood shields for openings.	\$9,298–15,354 per building (US, UK)	Days to a few weeks, depending on material application and size of building.	No (minimal disruption, unless extensive work required).
Dry Flood-Proofing (+2m)	Similar to +0.6m, but with stronger barriers and reinforcements to withstand higher water pressure.	\$14,105–36,695 per building (US)	Weeks, depending on complexity and structure type.	Possibly (if major modifications are required).
Wet Flood-Proofing (Basement, +0.6–2.7m)	Applying waterproof sealants, sump pumps, drainage improvements, raising utilities above flood level.	\$35–206 per m ² (US, Germany)	Days to a few weeks, depending on basement size and waterproofing method.	No (unless major excavation or retrofitting needed).
Wet Flood-Proofing (Residential, +0.6m)	Raising electrical sockets, using water-resistant materials, modifying interior walls and floors.	\$2,412–5,461 per building (US, UK)	Days to weeks, depending on extent of retrofitting.	No (can be done with minimal disruption).
Wet Flood-Proofing (Residential, +2.7m)	More extensive retrofitting including raising appliances, sealing walls, and modifying floor levels.	\$9,561–21,655 per building (US, UK)	Weeks, as more structural modifications are needed.	Possibly (depending on structural changes).

348 charitable sources were among the strongest predictors of remaining in place rather than
349 relocating. However, the relationship between a household’s economic status (income and
350 wealth) and out-relocation is complex. On one hand, households with fewer economic
351 resources may struggle to finance repairs, increasing the likelihood of relocation (Paul
352 et al., 2024). On the other hand, limited financial capacity can also constrain relocation
353 opportunities, as households may lack access to credit to purchase a new home or suf-
354 ficient income to afford alternative housing. As a result, some households may remain
355 in damaged homes despite wanting to leave. In general, we can conclude that residents
356 with greater financial resources tend to have greater capabilities when deciding whether
357 to relocate or remain.

358 *3.2.2 Place Attachment and Social Connections*

359 Place attachment is another factor influencing out-relocation. It refers to the emo-
360 tional and functional bond individuals form with their communities and has two key di-
361 mensions: place identity, which reflects how a community shapes an individual’s sense
362 of self, and place dependence, which describes how well the community fulfills practical,
363 everyday needs. Both Greer et al. (2019) and Paul et al. (2024) highlighted the role of
364 place attachment in reducing out-relocation among residents of hazard-exposed commu-
365 nities. Closely related to place attachment are social connections. Both Greer et al. (2019)
366 and Paul et al. (2024) found evidence that social connections influence out-relocation de-
367 cisions. Connections among family members, neighbors, or community organizations fos-
368 ter a sense of belonging and mutual support, which can lower the likelihood of perma-
369 nent relocation out of hazard-affected communities (Henry, 2013; Fraser et al., 2003; My-
370 ers et al., 2008; Nejat et al., 2016). Interestingly, Greer et al. (2019) noted that exten-
371 sive damage to the built environment can reduce place attachment. For instance, if a haz-
372 ard results in widespread destruction and the rebuilt environment differs significantly
373 from its pre-hazard state, some residents may feel disconnected and become more likely
374 to relocate.

375 *3.2.3 Risk Perception*

376 Risk perception is another factor influencing relocation in hazard-exposed commu-
377 nities. Both Greer et al. (2019) and Paul et al. (2024) found that high risk perception
378 contributes to permanent out-relocation. However, they noted that its significance re-
379 lative to other factors remains under-explored. Bakkensen and Barrage (2022) surveyed
380 households in Rhode Island, US, including residents of flood-exposed areas and residents
381 of regions not exposed to flooding (for residents of non-exposed areas, participants were
382 asked to imagine living in a flood-prone community). The study found that (1) residents
383 of flood-exposed communities were less concerned about flood risk compared to their non-
384 exposed counterparts, and (2) residents of exposed areas with higher concerns about fu-
385 ture flood risk were more likely to consider out-relocation in the near future. In line with
386 Bakkensen and Barrage (2022), Tonn and Guikema (2018) also found that risk percep-
387 tion is strongly influenced by past hazard experience. Generally, individuals who have
388 experienced a hazard in the past exhibit higher concerns about future risks. Moreover,
389 Tonn and Guikema (2018) additionally found that near-misses—instances where indi-
390 viduals narrowly avoid the impact of a hazard—can sometimes reduce risk perception.
391 Residents spared by the hazard may gain confidence that they will continue to be un-
392 affected in the future.

393 *3.2.4 Housing Tenure and Housing Type*

394 Two additional factors influencing out-relocation outcomes are housing tenure (own-
395 ing vs. renting) and housing type (e.g., detached single-family vs. multifamily buildings).
396 Regarding housing tenure, the literature consistently shows that homeowners are, on av-

397 erage, less likely to out-relocate after a destructive hazard compared to renters (Lee &
398 Van Zandt, 2019). Paul et al. (2024) identified several reasons for this: first, homeowners
399 are more likely to have developed stronger place attachment, as noted by Nejat et
400 al. (2018); second, they often have financial obligations tied to their property, such as
401 active mortgages; and third, government reconstruction aid has historically favored home-
402 owners in resource allocation for repairs (Dickinson et al., 2023). For housing type, Paul
403 et al. (2024) suggested that owners of detached single-family homes generally have greater
404 control over repairs and investments compared to owners of units in multifamily build-
405 ings. Limited control over the repair process in multifamily housing can result in pro-
406 longed recovery times, which, in turn, increases the likelihood of out-relocation.

407 **3.2.5 Demographics**

408 The effects of demographic characteristics, such as age, education level, and fam-
409 ily status, are nuanced and often underexplored. Greer et al. (2019) reviewed findings
410 from a limited number of studies on these characteristics, noting mixed and sometimes
411 contradictory results. Moreover, demographic characteristics can indirectly influence re-
412 location outcomes by shaping how individuals prioritize factors like economic concerns,
413 infrastructure, and community ties. For instance, Nejat et al. (2018), in a survey of 780
414 Oklahoma households conducted two years after they were impacted by an EF5 tornado,
415 found that older adults were more likely to prioritize economic factors like debt and in-
416 surance, whereas middle-aged respondents placed greater emphasis on infrastructure, pub-
417 lic safety and availability of essential services (e.g., schools).

418 **3.3 Community-level Characteristics**

419 Community characteristics are also critical in shaping relocation patterns in hazard-
420 affected areas. Community factors such as infrastructure, services, job availability, and
421 social networks, can influence both out-relocation and the ability to attract new residents.
422 In this section, we examine the community characteristics that have more influence on
423 relocation patterns.

424 **3.3.1 Infrastructure, Essential Services, and Job Availability**

425 The recovery of infrastructure (e.g., lifelines and streets) and essential services (e.g.,
426 groceries and schools) disrupted by a hazard is widely recognized in the literature as crit-
427 ical for community recovery (Paul et al., 2024; Chang et al., 2008). Utility outages, such
428 as water and power, can displace residents even when houses are structurally habitable
429 (Chang et al., 2008). Failure to restore infrastructure can lead to prolonged displacement
430 and prevent displaced residents from returning, thereby increasing the likelihood of per-
431 manent out-relocation. Restoring essential services is also important in preventing pro-
432 longed displacement. For example, (Burchfield, 2016) examined the case of Cordova, a
433 small town in Alabama (US) that was struck by two tornadoes on the same day in 2011,
434 resulting in the loss of most of its buildings and infrastructure. The town allocated pub-
435 lic resources to quickly reopen and maintain its only grocery store, even though depop-
436 ulation caused by widespread displacement had made the business financially unfeasi-
437 ble. Officials viewed the reopening as a crucial incentive for residents to remain in Cor-
438 dova and rebuild rather than relocate to another town. Similarly, job availability is a sig-
439 nificant factor influencing relocation patterns after a destructive natural hazard and through-
440 out the recovery phase (Kim & Oh, 2014; Landry et al., 2007; Wang et al., 2025). Anal-
441 yses from these studies suggest that job losses caused by hazards can drive permanent
442 out-relocation among current residents. Interestingly, Elliott (2015) also found that de-
443 structuring natural hazards activate also flows of in-relocation. They refuted a previous
444 hypothesis suggesting that these in-migrants are primarily driven by reconstruction-related
445 jobs, such as construction work (Pais & Elliott, 2008). Instead, they found that in-migrants

446 of different ethnicities typically joined job sectors their ethnic group already occupied
447 before the disaster.

448 The influence of infrastructure, services, and jobs on permanent relocation extends
449 beyond the disruption caused by natural hazards. They are considered amenities that
450 generally attract residents to communities. In hazard-affected communities, such ameni-
451 ties play a critical role in long-term recovery by helping retain current residents and at-
452 tracting new ones. For example, Cross (2014) studied US communities where over 50%
453 of structures were destroyed by a natural hazard. This study found that 50% of com-
454 munities without an elementary school experienced a population decline of more than
455 one-third in the decade following the hazard, compared to only 20% of communities with
456 an elementary school. The presence of elementary schools seems a key predictor of long-
457 term community stability, as communities with a higher proportion of residents in their
458 thirties and forties—those likely to have young children—tend to show greater growth
459 potential (Rosenthal, 2008). For these families, access to an elementary school represents
460 a strong attractor. The importance of schools in long-term recovery is further supported
461 by C. G. Burton (2015), who found a positive, statistically significant correlation between
462 the presence of schools and recovery outcomes in Mississippi Gulf Coast communities
463 (US) five years after Hurricane Katrina. Notably, Cross (2014) examined whether also
464 county courthouses help retain residents, for instance by acting as economic anchors through
465 employee salaries, local spending, and service procurement. However, no significant cor-
466 relation was found between the presence of a courthouse and post-hazard population trends.

467 Another example of the importance of services and infrastructure in attracting res-
468 idents is Paradise, California (US), which was razed by the 2018 Camp Fire (Mauhay-
469 Moore, 2024). Almost 90% of the town’s residents were displaced by the disaster. How-
470 ever, since 2020, its population has grown steadily, recently making it the fastest-growing
471 town in California and bringing it back to nearly half of its pre-fire level (of Finance, 2024).
472 To strengthen its appeal and draw new residents, Paradise is undertaking several ma-
473 jor infrastructure projects, including installing high-speed internet to attract remote work-
474 ers and constructing a sewage pipeline to replace individual septic systems. The town
475 also plans to develop a walkable downtown area, which local officials envision as the cen-
476 terpiece of its recovery efforts. Lastly, Cross (2014) found that communities within 25
477 kilometers of a metropolitan area were more likely to gain population in the decade fol-
478 lowing a natural hazard, while those over 100 kilometers away were more likely to ex-
479 perience population decline. This pattern confirms the role of essential services, infras-
480 tructure, and employment opportunities in shaping relocation patterns, as metropoliti-
481 tan areas generally offer a greater variety of them.

482 *3.3.2 Anchors of Social Networks*

483 Certain types of services, such as art and community centers, places of worship, and
484 social advocacy organizations, can strengthen social networks through community in-
485 volvement, thereby increasing place attachment. These services also provide critical sup-
486 port during periods of hardship, enhancing community resilience. For example, C. G. Bur-
487 ton (2015) found a positive, statistically significant correlation between the presence of
488 these services and recovery outcomes in Mississippi Gulf Coast communities (US), based
489 on five years of data following Hurricane Katrina. Similarly, Airriess et al. (2008) doc-
490 umented how the Mary Queen of Vietnam Church in New Orleans (US) mobilized so-
491 cial capital and networks to enhance the recovery of its community. Finally, Nejat et al.
492 (2019) provides a range of services identified in the literature that strengthen social con-
493 nections and support recovery, referring to them as “Anchors of Social Network”.

3.3.3 *Natural Characteristics*

Some favorable natural characteristics can also attract residents and influence in-relocation while, at the same time, be associated with increased exposure to natural hazards. A well-known example of the intersection between favorable natural characteristics and higher exposure to natural hazards is proximity to water, which increases exposure to flooding. Research on housing prices has consistently shown that homes closer to water bodies are typically more expensive than comparable properties located more inland (Jin et al., 2015). This price premium reflects higher demand from buyers seeking the natural amenity of waterfront living. The appeal of proximity to water extends beyond its aesthetic and recreational value. Access to rivers, lakes, and oceans promotes trade and productivity, attracting businesses and generating economic opportunities for residents (Rappaport & Sachs, 2003; Neumann et al., 2015). Similarly, the US population has grown significantly in the wildland-urban interface (WUI), a transitional zone between developed areas and natural landscapes that are often prone to wildfires. Rao et al. (2022) and Radeloff et al. (2018) found that the population in WUI areas roughly doubled between 1990 and 2010. The reasons for this growth in WUI regions are not yet fully understood. However, hypotheses suggest that these areas are attractive because of their affordability, access to natural settings, and recreational opportunities (Radeloff et al., 2018). Despite the occurrence of a wildfire potentially decreasing the natural attractiveness of WUI areas, studies in the national forests surrounding the Los Angeles metropolitan area have found that this decrease is only temporary (Garnache & Lupi, 2018).

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3.4 Policies and Government Intervention

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3.4.1 *In-Place Adaptation Measures*

The implementation of in-place adaptation measures can also affect relocation. First, government investments in risk reduction and preparedness, such as improved infrastructure and the organization of preparedness procedures, can enhance community resilience and make communities more attractive. For example, research on coastal property values in Massachusetts found that homes located behind seawalls experienced a 10% increase in value compared to otherwise similar properties, suggesting that protective infrastructure can make hazard-prone areas more desirable (Jin et al., 2015). Similarly, a Washington Post analysis suggests that even high-risk areas can attract residents if they implement adaptation measures that reduce risk and increase resilience (Coren et al., 2024). However, the increased attractiveness of hazard-prone areas due to risk-reduction measures can sometimes have negative consequences, such as the safe development paradox. The safe development paradox occurs when adaptation measures reduce perceived risk, encouraging development in hazard-prone areas and simultaneously lessening preparedness. The safe development paradox heightens exposure and amplifies potential losses during extremely rare events that exceed the protection level. One example is the Netherlands, where extensive development occurred in floodplains following the implementation of the Deltaworks flood protection program (Husby et al., 2014). When associated with flooding, this phenomenon is sometimes referred to as the “levee effect”. Fusinato et al. (2024) provides a comprehensive review of studies investigating the safe development paradox and presents substantial evidence supporting its occurrence. The safe development paradox is also linked to non-infrastructure adaptation measures, such as insurance. A vast body of literature explores the various effects of insurance on hazard-exposed communities, which lies beyond the scope of this review. Here, we highlight only one relevant aspect: in some cases, insurance premiums may not fully reflect actual future risk, for instance when subsidized by the government. When premiums do not reflect true risk, they can incentivize risky behaviors or discourage additional protection, such as retrofitting buildings to reduce risk, thereby perpetuating the safe development paradox (Liu et al., 2024).

546 The second interaction between in-place adaptation measures and relocation pat-
547 terns occurs when requirements to implement adaptation measures force out-relocation
548 of existing residents. When such measures become mandatory—often as part of recon-
549 struction efforts following a destructive event—their high costs can compel some home-
550 owners to leave. For example, FEMA’s Title 44 (FEMA, 2025) outlines the requirements
551 for properties in flood-prone areas to meet specific elevation standards. The regulation
552 mandates that homes within Special Flood Hazard Areas (SFHA) that sustain damage
553 exceeding 50% of their pre-flood market value must be retrofitted to comply with ele-
554 vation requirements. Noncompliance prevents homeowners from obtaining the construc-
555 tion permits needed to lawfully carry out repairs. Barber (2024), reporting in *The New*
556 *York Times*, highlighted the case of Pittsburg, Florida, a community highly exposed to
557 hurricane-induced storm surge. The article describes how several residents, unable to af-
558 ford the mandatory home elevations after suffering damages from Hurricane Helene in
559 2024, are being forced to sell their homes. McCall et al. (2024) interviewed residents of
560 Plaquemines Parish, Louisiana (US), a low-lying area highly exposed to flood risks. Their
561 findings indicate that FEMA requirements to elevate flood-damaged homes risk caus-
562 ing significant out-relocation, as most residents cannot afford to elevate their houses. The
563 primary barrier to compliance is financial, but other challenges include the high propor-
564 tion of residents living in mobile homes and trailers, which are difficult to elevate with-
565 out compromising their mobility. Additionally, home elevation creates physical acces-
566 sibility issues for older and disabled individuals. The study also highlights how residents
567 unable to meet elevation requirements may struggle to sell their properties. Federally
568 backed mortgages require flood insurance, and premiums for non-elevated properties can
569 be prohibitively expensive. Consequently, residents attempting to sell non-compliant prop-
570 erties may face a significantly reduced pool of potential buyers. Rising flood insurance
571 costs can simultaneously force current residents to leave and hinder their ability to ex-
572 tract equity by selling their homes. This finding underscores how both infrastructure mea-
573 sures, such as home elevation, and non-infrastructure measures, such as flood insurance,
574 can impact relocation patterns. Similar requirements also apply to other types of haz-
575 ards. For example, in wildfire-prone areas, California Chapter 7A Building Code (California
576 Department of Housing and Community Development, 2010) mandates the use of fire-
577 resistant materials for roofing, siding, and decking in new construction and significant
578 renovations. However, the effects of such mandatory measures on relocation remain under-
579 explored in the literature.

580 *3.4.2 Buyouts*

581 Buyouts—the voluntary or mandatory purchase of properties in hazard-prone ar-
582 eas by the government—are a common policy tool for reducing long-term risk, partic-
583 ularly for flooding (New York City Build It Back Program, 2018). In some cases, buy-
584 out programs prohibit reconstruction on acquired land and require its conversion into
585 open space. In other instances, properties are sold back to developers with the require-
586 ment to implement stricter risk-reduction measures, such as increasing base floor eleva-
587 tions. Buyouts can be implemented at various scales, ranging from individual proper-
588 ties to entire neighborhoods or communities. The impact of buyouts on neighboring prop-
589 erties is mixed. On one hand, converting acquired land into parks or well-maintained open
590 spaces can enhance community desirability (Pierce Holloway & BenDor, 2023). On the
591 other hand, large-scale buyouts may signal high risk to potential home-buyers, disrupt
592 social cohesion, and reduce overall community appeal (Binder et al., 2020; Hashida &
593 Dundas, 2023). The reviewed studies highlight the importance of a clear strategy for re-
594 purposing acquired land, along with transparent communication with the public, to min-
595 imize negative effects on neighboring properties. Uncertainty about the future use of bought-
596 out land can increase stress among remaining residents, prompting further out-relocation,
597 and deterring potential new residents from relocating into the neighborhood.

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3.4.3 *Post-hazard Economic Assistance*

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Finally, we address the effects of post-hazard assistance, which can be classified into two main categories: aid for recovery, such as repair assistance for homeowners and temporary living support for displaced individuals, and economic stimuli. The effects of aid for recovery in retaining residents and reducing out-relocation were discussed in the previous section (Nejat & Ghosh, 2016). Regarding economic stimuli, Pais and Elliott (2008) noted that after a destructive natural hazard in the US, federal funds made available for recovery are often partially utilized by local stakeholders, such as property and business owners, to foster local economic development. These efforts aim to attract further investment, boost the local economy to levels exceeding pre-hazard conditions, and, as a result, encourage in-relocation of new residents.

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The factors discussed in this section represent only a subset of the many drivers that influence relocation outcomes in conjunction with natural hazards. Our aim is not to provide an exhaustive list but to emphasize that relocation patterns are shaped by multiple, often intertwined factors, as highlighted in the existing literature (Black et al., 2011). These drivers can sometimes act in opposite directions: for example, proximity to water may attract residents due to its amenity value while simultaneously exposing them to increased flood risk. In other cases, relocation drivers can cascade, such as when hazards disrupt jobs, triggering further economic impacts that influence relocation decisions. Additionally, the same factor can have dual effects: for instance, destruction caused by natural hazards may prompt out-relocation among residents seeking to reduce future risks, while simultaneously driving redevelopment efforts and economic stimuli that attract new residents.

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4 **Socio-Economic and Demographic Changes in Hazard-Exposed Communities**

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In this section, we analyze studies that investigate the socio-economic and demographic changes driven by hazard-induced relocation in exposed communities. We identify three primary domains of change investigated by the literature: population size, socio-economic composition, and housing prices (Fig. 3).

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4.1 **Changes in Population Size**

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Here, we examine the long-term effects that natural hazards may have on a community's population size. In cases where a community's population size has remained stable over time, we can ask whether a natural hazard (or series of hazards) might cause a population decrease or increase in the long term. Another scenario is when a community is already experiencing population change, such as growth driven by net in-relocation. In this case, we could ask ourselves whether one or more natural hazards can alter these ongoing trends. For example, a community experiencing steady growth over the past decade might see a slowed growth rate or even a reversal if impacted by an intense hazard event. We review both specific case studies and broader statistical analyses that address these questions.

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First, we examine a case study by Smith and McCarty (2011) focusing on the aftermath of the 2004 hurricane season in Florida, a series of events that severely damaged approximately 324,000 residential units and temporarily displaced almost 1.6 million people. This study analyzed population data at both the county and city levels, focusing on 11 counties affected by multiple hurricanes during the season. Of these, five counties experienced population losses from 2004 to 2005. Before the hurricanes, all five had been growing, and by 2008, each had surpassed its pre-hurricane population level. The study also examined seven incorporated cities within these five counties, each of which had been growing before the hurricanes as well. These cities saw population declines from 2004

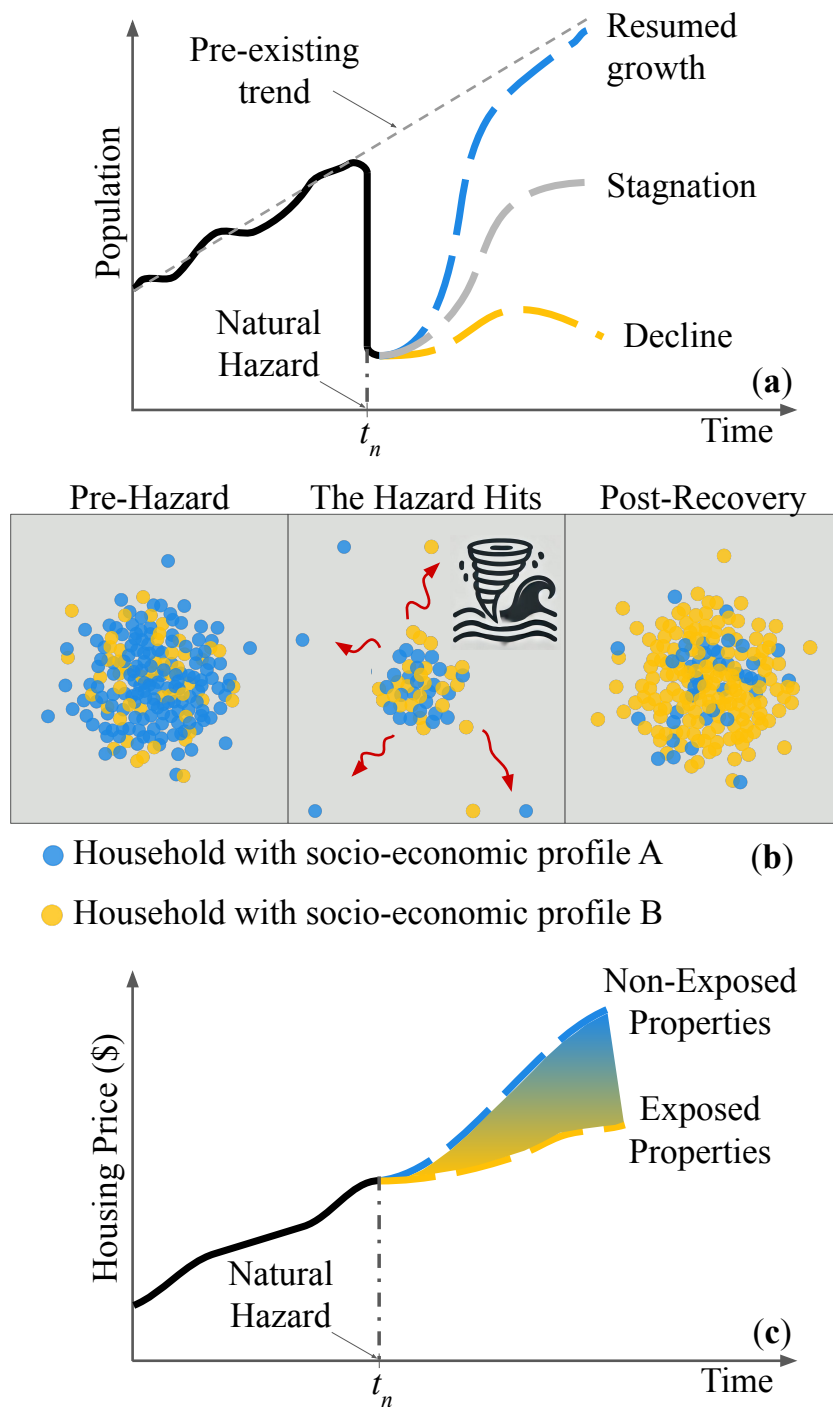


Figure 3. Schematic representation of three domains of change in hazard-exposed communities: (a) Population size, showing a sudden drop after a natural hazard event followed by different possible trajectories. (b) Socio-economic composition, illustrating shifts in population characteristics due to out- and in-relocation. (c) Housing prices, depicting distinct trends for exposed and non-exposed properties after the hazard event.

647 to 2005 but resumed growth afterward. According to the 2010 US Census, four of the
648 cities had exceeded their 2004 population levels by 2007. The study also references the
649 impacts of Hurricane Andrew in 1992, noting that while severe initial impacts led to sig-
650 nificant population declines in areas within Miami-Dade County, such as Florida City
651 and Homestead, these locations eventually exceeded their initial population figures by
652 the end of the decade. The paper concludes that despite the immediate disruptions caused
653 by the 2004 hurricanes, there were no lasting impacts on the long-term population trends
654 within the examined communities. This case study, while insightful, provides specific out-
655 comes from a limited dataset and cautions against broad generalizations without further
656 comprehensive analysis.

657 A more comprehensive study is provided by Fussell et al. (2017). In their paper,
658 the authors analyzed the impact of hurricanes and tropical storms on future population
659 growth in US counties from 1980 to 2012 by developing a statistical model. They an-
660 alyzed county-level data annually, using population growth trends and the number and
661 intensity of hazards over the previous decade as independent variables, population growth
662 over the next three years as the dependent variable, and population density as a con-
663 trol. They found that natural hazards-related predictors generally have no significant
664 effect on future population growth compared to past population trends, except for high-
665 density, growing counties where natural hazards appear to stimulate population growth
666 over the subsequent three years. An explanation provided by the authors for this phe-
667 nomenon could be that reconstruction resources have a boosting effect on the local econ-
668 omy. One consideration with this analysis is that it was conducted at the county level,
669 which may be too coarse to capture the nuanced impacts of natural hazards. For instance,
670 when Hurricane Sandy struck New York City, only the coastal areas were flooded. In Kings
671 County (Brooklyn), for example, less than 13% of the residential units were located within
672 the inundated zones (Department of Small Business Services, 2024; Department of City
673 Planning, 2012). Therefore, analyzing the entire county may not accurately reflect the
674 localized effects of the hazard. Moreover, their analysis relies on a three-year projection
675 of population changes, though recovery can extend further with later adjustments. Re-
676 peating the analysis with a longer time horizon could capture effects that emerge beyond
677 three years.

678 Cross (2014) adopted a finer geographical focus, examining US communities where
679 more than 50% of structures were destroyed by disasters between 1992 and 2008. This
680 selection allowed for a more precise understanding of disaster impacts on localized pop-
681 ulation dynamics. Cross found that communities previously experiencing population de-
682 clines were nearly three times more likely to face further substantial declines post-disaster,
683 compared to communities that were previously growing. The author concluded that nat-
684 ural disasters are more likely to accelerate existing demographic trends rather than cause
685 drastic reversals. Nonetheless, there were instances where communities defied this pat-
686 tern, with previously growing communities turning to decline, and vice versa. This find-
687 ing aligns with the previous discussion that relocation outcomes also depend on a broader
688 set of context-specific factors.

689 Another study supporting the thesis that natural disasters do not drastically al-
690 ter population trends but may accelerate existing patterns is provided by Vigdor (2008),
691 focusing on New Orleans after Hurricane Katrina. The author analyzed population data
692 up to two years after the hurricane, when New Orleans' population was slightly above
693 50% of its pre-hazard level, and questioned whether the city will ever fully recover its
694 population. The study examined several cities affected by catastrophic events in the 20th
695 century, both natural and man-made. In each case, cities that were growing before the
696 event regained their population and continued to expand. The only exception is Dres-
697 den, which was already losing population before being nearly destroyed during WWII.
698 The article then explores historical trends in New Orleans, noting that the city grew in
699 the 1800s as a major port but began declining in the second half of the 20th century due

700 to stagnation of the local economy. The author emphasizes that New Orleans was already
701 experiencing a steady population decline before Katrina. However, lower housing costs—
702 due to a surplus accumulated in past decades—helped slow this trend. The hurricane
703 eliminated this surplus, removing the low-cost housing incentive that had retained some
704 residents. As a result, many did not return. Fig. 4 illustrates population trends in New
705 Orleans. The left plot focuses on the years immediately after Katrina, showing that five
706 years after the disaster, the city’s population remained about 20% below pre-hurricane
707 levels. The right plot presents data from 1970 to 2023, demonstrating that New Orleans
708 had been in steady decline even before the hurricane. After five years of recovery follow-
709 ing the hurricane, the city appears to have resumed this gradual decline. These data, up-
710 dated through 2023, confirm the author’s predictions made just two years after the dis-
711 aster.

712 Indaco and Ortega (2024) analyzed the correlation between hazard frequency and
713 population growth in the US from 1990 to 2020. The study examines population changes
714 at both the county and census tract levels and compares different areas at the national
715 level as well as within commuting zones. According to their analysis, areas with higher
716 hazard frequency experienced greater population growth compared to low-frequency haz-
717 ard areas, both nationally and within commuting zones. These results may suggest that
718 characteristics making areas more prone to natural hazards, such as proximity to forests
719 (for wildfires) or waterways (for flooding), might also enhance their attractiveness, and
720 their appeal outweigh the negative effects of natural hazards. The authors then expanded
721 the analysis by introducing several control variables, providing further insights. First,
722 by controlling for housing density, they found that the higher growth rates in high-frequency
723 hazard areas are primarily observed in densely populated regions, while in low-density
724 areas, high hazard frequency seems to cause population decline. This finding suggests
725 that in areas already attracting population, other factors outweigh the effect of natural
726 hazards on population changes, while in less attractive areas, natural hazards acceler-
727 ate population decline. Second, by controlling for hazard type, they found that within
728 commuting zones, only Census tracts affected by coastal flooding grew at a slower rate
729 compared to those less affected. The authors attribute this pattern to the predictable
730 spatial boundaries of coastal flooding, which allow residents to reduce their exposure by
731 relocating within the same commuting zone.

732 The findings described above primarily concern the effects of intense, rare events.
733 In contrast, slow-onset, recurrent phenomena—such as tidal flooding exacerbated by SLR—
734 may lead to different outcomes, as discussed in the previous section. For example, L. Perch-
735 Nielsen et al. (2008) investigated cases of community abandonment driven by both sud-
736 den, destructive flooding and gradual, long-term SLR. They found no instances of aban-
737 donment from single-event flooding, regardless of intensity, but identified three cases linked
738 to chronic flooding exacerbated by SLR: Holland Island (Chesapeake Bay, Maryland, US),
739 the Caspian Sea coast (particularly Kazakhstan), and Brownwood (a peninsula near Hous-
740 ton, Texas, US). Holland Island experienced approximately 20 cm of relative SLR be-
741 tween 1850 and 1920, leading to erosion and gradual land loss. Despite efforts to remain,
742 the island was abandoned in 1920 as land loss and population decline made local services
743 unsustainable. In the Caspian Sea region, SLR inundated extensive coastal areas between
744 1978 and 1995, displacing thousands of residents. Lastly, Brownwood faced worsening
745 tidal flooding that caused its complete abandonment, due to land subsidence from ground-
746 water extraction. Relative SLR caused by land subsidence also threatens several major
747 coastal cities worldwide, including Jakarta, Ho Chi Minh City, Bangkok, Dhaka, New
748 Orleans, Venice, and Tokyo (Erkens et al., 2015). In these cities, geological processes and
749 anthropogenic factors, particularly groundwater extraction, combined with SLR, are in-
750 creasing tidal flooding frequency and intensity. Jakarta, for example, is subsiding at rates
751 of up to 10–20 cm per year, prompting the Indonesian government to plan the capital’s
752 relocation. SLR poses an even greater threat to islands, where the option of inland re-
753 treat is limited. Hauer et al. (2020) examined the vulnerabilities of atoll nations such

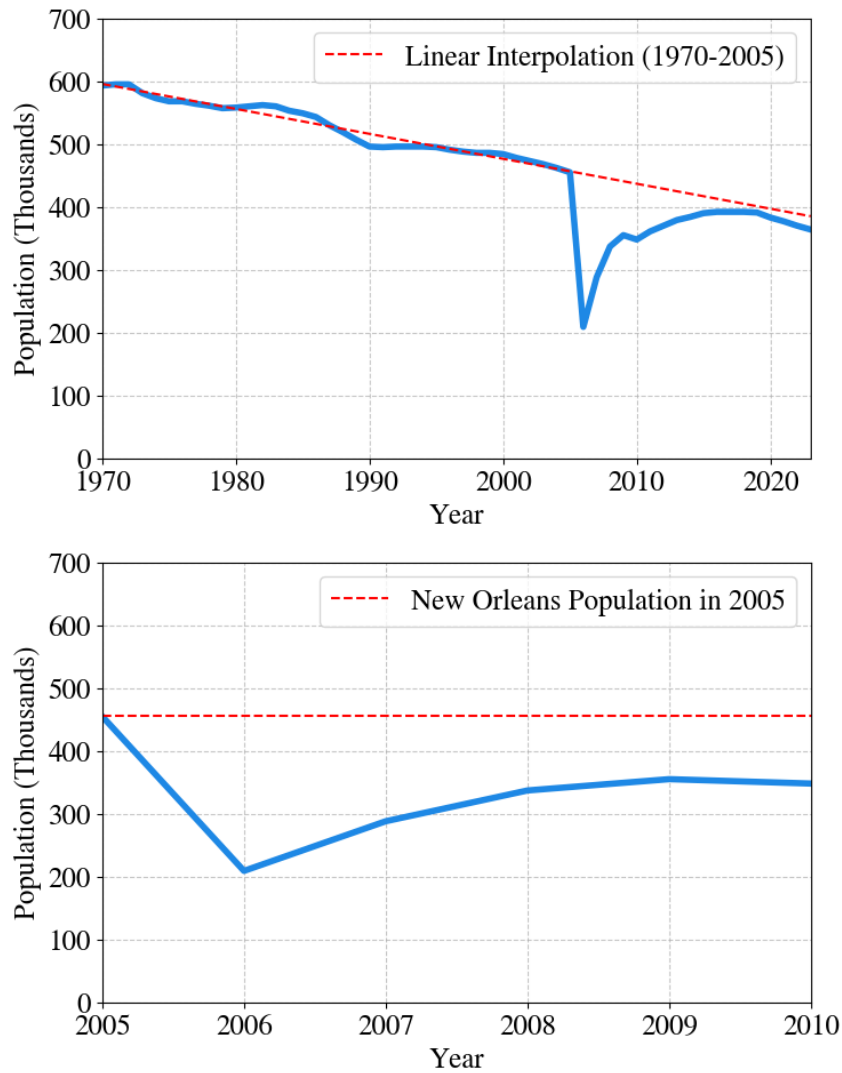


Figure 4. Population trends in New Orleans, illustrating both short- and long-term impacts of Hurricane Katrina. The top plot shows the immediate effects from 2005 to 2010, with a sharp population decline after the hurricane in 2005, followed by partial recovery, reaching about 80% of pre-hurricane levels by 2010. The bottom plot presents a longer-term view from 1970 to 2023, indicating a steady population decline that predates Katrina. As shown in the bottom plot, after a five-year recovery period, the population trend resumed its gradual downward trajectory, consistent with historical patterns. U.S. Census Bureau, Resident Population in Orleans Parish, LA [LAORLE0POP], retrieved from FRED, Federal Reserve Bank of St. Louis (U.S. Census Bureau, n.d.).

754 as the Maldives, Tuvalu, Kiribati, and the Marshall Islands, where SLR is causing in-
755 undation, freshwater scarcity, and soil salinization. In response, some atoll nations are
756 adopting planned relocation policies. Islands also appear more prone to net population
757 loss following natural hazards in general, not only SLR. Two notable cases are Kauai,
758 Hawaii (US), after Hurricane Iniki (1992), and Montserrat (British Overseas Territory
759 in the Caribbean), following volcanic eruptions in the mid-1990s. Coffman and Noy (2012)
760 showed that Hurricane Iniki caused severe long-term economic disruption on Kauai, re-
761 sulting in approximately 12% lower population two decades after the hurricane compared
762 to projections had the disaster not occurred. In Montserrat, volcanic eruptions begin-
763 ning in 1995 forced the near-total abandonment of the island’s southern two-thirds, in-
764 cluding the capital, Plymouth (McLeman, 2011). Since then, the island’s population has
765 remained relatively stable, without significant recovery or further decline.

766 Finally, the literature has also shown that natural hazards can act as a pull factor,
767 something counterintuitive. A study by Elliott (2015) investigated empirically the
768 role of natural hazards as push and pull factors on relocation. They conducted a detailed
769 household-level analysis of relocation patterns across the US, using a sample of house-
770 holds from diverse geographic regions defined by Public Use Microdata Areas (PUMAs).
771 Focusing on the period between 1995 and 2000, the study explored the correlation be-
772 tween relocation and the frequency and intensity of natural hazards—quantified in terms
773 of property losses—in these regions. The findings reveal a statistically significant posi-
774 tive correlation between the intensity of natural hazards and the out-relocation from af-
775 fected areas (push factor). Interestingly, the analysis also identifies a positive correla-
776 tion between in-relocation and property losses due to natural hazards, suggesting that
777 such events can also act as pull factors. This pull effect is particularly pronounced among
778 Asian and Latino populations and persists even after controlling for existing foreign com-
779 munities at the destinations. Notably, the study refutes an earlier hypothesis by Pais and
780 Elliott (2008), which suggested that in-relocation is primarily driven by job opportuni-
781 ties in disaster recovery efforts. Instead, they found that residents relocating into hazard-
782 impacted areas tend to enter job sectors their ethnic groups were already engaged in be-
783 fore the hazardous event. However, the study did not explain this observed increase in
784 in-relocation.

785 In summary, large-scale statistical analyses of US data generally indicate that natu-
786 ral hazards do not significantly alter ongoing population trends but can sometimes ac-
787 celerate them. However, finer-scale analyses (e.g., at the US Census tract level) show that
788 certain hazards, such as coastal flooding, can slow population growth. Case studies fur-
789 ther suggest that slow-onset, chronic events like SLR have greater potential to cause net
790 population loss compared to rare, destructive events. This effect is particularly evident
791 for islands, which generally tend to be more prone to depopulation due to natural haz-
792 ards. Lastly, the literature highlights that natural hazards can sometimes act as pull fac-
793 tors, attracting new residents despite increased risks, particularly in areas with desirable
794 amenities.

795 4.2 Changes in Socio-Economic and Demographic Status

796 Natural hazards often cause (or influence) shifts in population characteristics through
797 in- and out-relocation. One potential outcome identified in literature is the increase of
798 wealthier residents following a destructive event. For example, Graff Zivin et al. (2023)
799 analyzed mortgage application data in Florida from 2000 to 2016, finding that hurricane-
800 affected areas tend to attract wealthier homebuyers. They attributed this phenomenon
801 to a sudden decrease in housing supply caused by the destruction from the hazard, which
802 in turn intensifies competition among potential buyers, with wealthier individuals out-
803 bidding those with lower incomes. Since homeownership typically involves long-term com-
804 mitments, this demographic shift can potentially lead to enduring socio-economic changes
805 within the affected communities, characterized by a higher proportion of homes being

806 occupied by wealthier households post-disaster. A similar mechanism influences rental
807 housing markets, but socio-economic changes are typically transient due to shorter ten-
808 ancy durations. However, permanent shifts can occur if the rental housing stock is not
809 fully restored. This was evident in New Orleans, where a 2021 study by The Data Cen-
810 ter (Plyer, 2021) found that, 15 years post-Hurricane Katrina, only five neighborhoods
811 had populations less than 50% of their pre-Katrina levels. Four of these neighborhoods
812 had large public housing complexes that were demolished and redeveloped into lower-
813 density, mixed-income dwellings post-hurricane, permanently altering the socio-economic
814 fabric of these areas. Adding to the empirical evidence, van Holm and Wyczalkowski (2019)
815 further explored gentrification after natural hazards by examining neighborhoods in New
816 Orleans from 2000 to 2015. They found that neighborhoods with greater damage from
817 Hurricane Katrina were more likely to undergo gentrification, as defined by an increase
818 in real housing prices and the percentage of residents with college education.

819 However, the phenomenon of post-disaster gentrification is not universally consist-
820 ent. Other research has documented contrasting scenarios where natural disasters have
821 led to stagnation in wealth or even exacerbated poverty conditions in affected neighbor-
822 hoods. For example, referring back to van Holm and Wyczalkowski (2019), not all New
823 Orleans neighborhoods predisposed to gentrification in 2000 followed this path by 2015.
824 Neighborhoods such as the Lower Ninth Ward and Hollygrove, despite suffering severe
825 damages, remained economically depressed and did not experience gentrification, accord-
826 ing to the study. Zhang (2012) examined the impact of Hurricane Andrew on five cities
827 in Miami-Dade County using parcel-level data from 1991 (one year before the hurricane)
828 to 2000 (eight years after). He employed a discrete-time hazard model to predict the tran-
829 sition of parcels from residential to abandoned, using block-level socio-economic char-
830 acteristics and the proximity to other abandoned parcels as independent variables, while
831 also controlling for damage level and building age. The study reveals that, independent
832 of damage and age, the odds of a property becoming vacant were 67% lower in middle-
833 class neighborhoods compared to poorer ones. Moreover, the analysis showed that prox-
834 imity to an abandoned parcel significantly increased the likelihood of a property becom-
835 ing abandoned. These findings suggest that in some of the communities with high poverty
836 rates, the damage caused by Hurricane Andrew, instead of attracting new, wealthier res-
837 idents, further depressed socioeconomic conditions.

838 The investigative journalism piece *In Arms' Way* (Lubben et al., 2022) further il-
839 lustrates how repeated natural hazards can compound socio-economic challenges in vul-
840 nerable communities. The article reports the struggles of residents in flood-prone areas,
841 who face significant financial losses when attempting to relocate. For example, a resi-
842 dent of Smithfield, Virginia (US), after enduring multiple floods, was forced to sell her
843 home for only \$39,000 and subsequently obtained a new mortgage, to buy a \$136,000
844 new house in a safer area. Another case from Freeport, Illinois, involves a homeowner
845 who attempted repairs on her home, valued at just \$7,000. Local building codes required
846 that renovations exceeding 50% of the property's assessed value meet flood protection
847 standards, and even minor repairs would have surpassed this threshold, necessitating costly
848 upgrades that were financially unfeasible. This scenario, referred to as a 'poverty trap'
849 (Black et al., 2013), demonstrates how natural hazards can sometimes deepen poverty
850 within affected communities.

851 In summary, both scientific research and investigative journalism document dual
852 outcomes in communities exposed to natural hazards. In some cases, affected commu-
853 nities attract wealthier residents after experiencing a destructive event, leading to gen-
854 tification and socioeconomic uplift. In others, these events exacerbate existing poverty,
855 trapping residents in worsening conditions. Based on the reviewed studies, the likelihood
856 of either scenario appears to depend more on factors unrelated to the hazard itself, such
857 as the inherent attractiveness of the affected location. This conclusion aligns with the
858 previous section, where we discussed the role of community characteristics in attract-

859 ing and retaining residents (Cross, 2014). This conclusion is also supported by Elliott
860 and Pais (2010), who compared the effects of Hurricane Andrew on two communities:
861 Miami, a densely urbanized area, and southwestern Louisiana, a more rural region. The
862 study found that in Miami, long-term recovery displaced socially vulnerable populations
863 from the hardest-hit areas, whereas in southwestern Louisiana, recovery processes con-
864 centrated these vulnerable groups within the hardest-hit zones. Therefore, we can con-
865 clude that in generally more attractive communities, natural hazards can displace poorer
866 residents, creating opportunities for wealthier individuals to move in. Conversely, in stag-
867 nating or economically depressed areas, the destruction caused by natural hazards can
868 further reduce attractiveness, deepening pre-existing poverty. Finally, there is a lack of
869 scientific literature examining socio-economic changes in response to chronic, low-intensity
870 events like tidal flooding.

871 4.3 The Housing Market

872 A large body of literature, primarily from the field of economics, examines how nat-
873 ural hazards affect housing prices. Although housing prices are not a socio-demographic
874 characteristic per se, they can shape a community’s socioeconomic composition. For in-
875 stance, if housing prices decline in high-exposure areas relative to safer ones, lower-income
876 households may be drawn to these areas, increasing the concentration of vulnerable pop-
877 ulations in hazard-prone neighborhoods. This pattern, for example, has been observed
878 in Los Angeles, California (US), where minority households (Black and non-Black His-
879 panic) are more likely than non-Hispanic Whites to reside in areas exposed to fluvial flood-
880 ing (Sanders et al., 2023). The literature identifies three main ways in which natural haz-
881 ards may influence housing prices. First, destructive events can temporarily raise prices
882 by reducing overall housing supply (Figure 5 *a*). Second, after an intense, rare event, prices
883 in more exposed areas suffer a sudden discount relative to less exposed ones. This dis-
884 count appears to be temporary, gradually vanishing over time (Figure 5 *b*). Third, in the
885 case of chronic hazards like SLR and tidal flooding, more exposed areas tend to appre-
886 ciate less, leading to persistent and increasing price differentials (Figure 5 *c*). However,
887 despite these discounts, some homebuyers may underestimate future risks, inflating prices
888 beyond their fundamental value and increasing the risk of price bubbles. The following
889 section reviews studies that explain these mechanisms.

890 Natural hazards can temporarily reduce housing supply, leading to short-term price
891 increases (Figure 5 *a*). According to the law of supply and demand, a drop in available
892 housing raises prices until the damaged stock is restored. Studies examining average hous-
893 ing prices at the community level, without distinguishing between exposure levels, sup-
894 port this trend. For instance, Graff Zivin et al. (2023) analyzed residential sales in Florida
895 following a hurricane and found that average prices temporarily rise, typically for 2–3
896 years. They also observed that mortgage applicants during this period tend to be wealth-
897 ier, potentially contributing to gentrification in affected areas. Murphy and Strobl (2010)
898 compared post-hurricane housing prices with projected prices had the hurricane not oc-
899 curred, finding similar results. They reported that house prices typically rise by 3–4%
900 three years after a hurricane, though this effect gradually fades over time. Staer and LaCour-
901 Little (2016) also documented rising housing prices in Christchurch, New Zealand, fol-
902 lowing the 2011 earthquake. Similarly, Vigdor (2008) reported sharp increases in both
903 sale prices and rents in New Orleans immediately after Hurricane Katrina. Although Graff Zivin
904 et al. (2023) accounted for a home’s proximity to a hurricane’s path, future hurricanes
905 are spatially unpredictable. Within the same geographic region, proximity to a past hur-
906 ricane does not necessarily indicate higher future exposure, as future hurricanes can fol-
907 low unpredictable trajectories. Murphy and Strobl (2010), Staer and LaCour-Little (2016),
908 and Vigdor (2008) analyzed price changes at the city level without differentiating between
909 properties with different exposure levels. Therefore, these studies confirm overall price
910 increases in affected communities, but they do not clarify how hazards impact more ver-
911 sus less exposed areas.

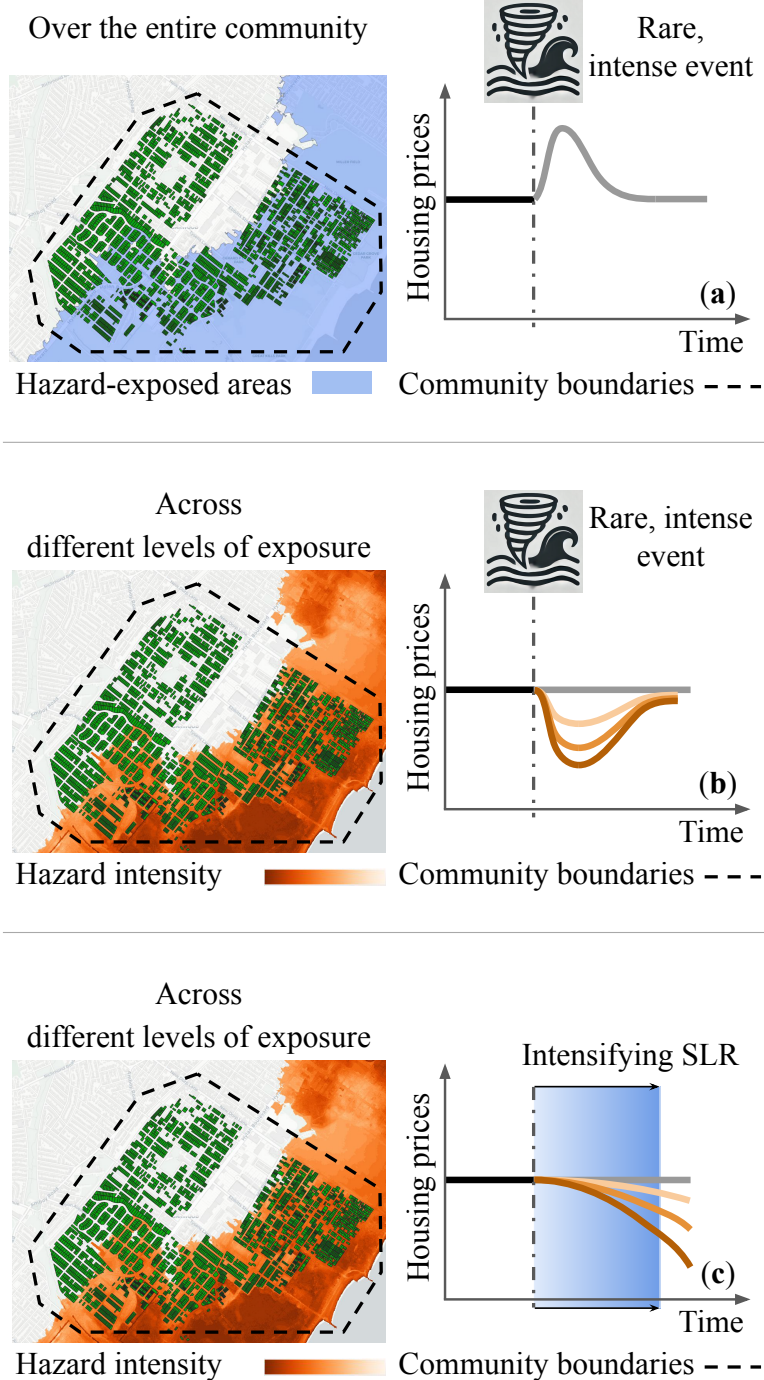


Figure 5. Effects of natural hazards on housing prices. (a) After a destructive hazard, overall housing prices rise due to supply shortages, then return to baseline as housing stock recovers. (b) More exposed homes decline in relative value compared to less exposed ones, but prices realign over time if the event is a single, intense occurrence. (c) For recurrent, lower-intensity hazards (e.g., sea level rise and tidal flooding), the price gap between more and less exposed homes persists and grows over time.

912 When controlling for different exposure levels, natural hazards tend to reduce hous-
913 ing prices in the most exposed areas relative to less exposed ones (Figure 5 *b*). Relative
914 price discounts in high-exposure zones have been observed after various hazards, includ-
915 ing flooding (Ortega & Taspinar, 2018; Bin & Polasky, 2004), earthquakes (Jung & Smith,
916 2022; Shi & Naylor, 2023), wildfires (Adachi & Li, 2023; Koo & Liang, 2022), and tor-
917 nadoes (Cho et al., 2022). For instance, Ortega and Taspinar (2018) found that non-damaged
918 properties within Hurricane Sandy’s flooded zones in New York City experienced an 8%
919 price discount compared to similar properties just outside the inundated area. This find-
920 ing suggests a market adjustment to the increased perceived risk of future flooding. A
921 similar effect has been observed after the public release of updated risk ratings, such as
922 the inclusion of properties in flood hazard areas following a flood map update. Gibson
923 and Mullins (2020) compared property prices in New York City before and after FEMA’s
924 2013 flood map revision. They found that properties newly designated as flood-prone
925 appreciated about 12% less over four years than similar properties outside the updated
926 maps. Donovan et al. (2007) reported a comparable trend in Colorado Springs, where
927 home prices declined after the local fire department publicly rated the wildfire risk of
928 35,000 houses. These findings suggest that both direct hazard events and official risk des-
929 ignations increase risk perception among homebuyers, reducing demand and lowering prop-
930 erty values in high-exposure areas.

931 However, housing price responses to natural hazards vary across communities, as
932 factors beyond hazard exposure also influence demand. The reviewed literature identi-
933 fies three key factors that interact with natural hazards in shaping housing prices: prox-
934 imity to urban centers, natural amenities, and risk disclosure policies. For example, Cheung
935 et al. (2016) examined housing price declines in Oklahoma following seismic shocks. They
936 found that price drops correlate with earthquake intensity but are less pronounced in ur-
937 ban areas than in rural ones. Urban housing remains more attractive due to factors dis-
938 cussed in the previous section, such as greater economic opportunities. Even in areas ex-
939 periencing strong earthquakes, these advantages help sustain demand, mitigating price
940 declines. Natural amenities can also offset the negative effects of hazard exposure on hous-
941 ing prices. In Los Angeles, Sanders et al. (2023) found that minority households (Black
942 and non-Black Hispanic) are more likely than non-Hispanic Whites to reside in areas ex-
943 posed to fluvial flooding. However, non-Hispanic Whites are more concentrated in coastal
944 areas, despite their higher exposure to coastal flooding. This suggests that the amenity
945 value of coastal proximity outweighs flood risk for some buyers. Similarly, Bin and Kruse
946 (2006) and Bin et al. (2008) analyzed property sales in Carteret County, North Carolina
947 (US). They found that floodplain properties are generally discounted compared to sim-
948 ilar homes outside flood zones, but mainly for inland flooding. In contrast, coastal prop-
949 erties command higher prices despite their increased exposure to coastal flooding, con-
950 firming the role of natural amenities in shaping housing demand. The third factor in-
951 fluencing housing demand is the strength of risk disclosure laws. Research shows that
952 stricter disclosure requirements lead to greater price discounts for properties in officially
953 designated high-exposure areas, such as FEMA’s Special Flood Hazard Areas (SFHAs).
954 For example, Gourevitch et al. (2023) analyzed price discounts for SFHA-designated prop-
955 erties across the US coastline, controlling for state flood disclosure laws and local climate
956 concern. They found that SFHA inclusion reduces property values by 2.5% to 9.7%, with
957 stricter disclosure laws and greater climate awareness associated with larger discounts.
958 Similarly, Pope (2008) compared housing prices before and after the implementation of
959 the 1996 Residential Property Disclosure Act, which mandated disclosure of flood risk
960 in North Carolina (US). Before the law, there was no significant price difference between
961 SFHA and non-SFHA properties, but after its passage, SFHA properties experienced a
962 4% relative price discount. Ma et al. (2023) found a similar effect for wildfire risk dis-
963 closure in California (US), observing that properties in areas where wildfire risk must
964 be disclosed sell for approximately 4.3% less than comparable properties in unregulated
965 areas. These findings suggest that formal risk disclosure increases buyer awareness, re-
966 ducing demand and lowering prices in high-risk zones.

967 In some cases, the initial drop in housing prices following an intense hazard event
968 diminishes over time and may eventually disappear. For example, Bin and Landry (2013)
969 found that housing prices in Pitt County, North Carolina (US), dropped in floodplains
970 after Hurricanes Fran (1996) and Floyd (1999) but returned to pre-disaster levels within
971 six years. Similar trends have been documented for other hazards, including fluvial flood-
972 ing (Atreya et al., 2013), earthquakes (Yasuda et al., 2019), and tornadoes (Cho et al.,
973 2022). The disappearance of price differentials over time suggests that risk perception
974 adjusts, either due to belief updates among long-term residents or the arrival of new buy-
975 ers unfamiliar with past hazards. Bakkensen and Barrage (2022) used an agent-based
976 model to show that even a small share of homebuyers with overly optimistic risk per-
977 ceptions can drive up prices, reducing the gap between exposed and non-exposed areas.

978 As previously discussed, among natural hazards, flooding is one of the most spa-
979 tially predictable. While hurricanes can follow various paths after landfall, flood expo-
980 sure is largely determined by topography and proximity to water bodies. Due to this pre-
981 dictability, some studies examined housing price differentials within SFHA, focusing on
982 the effects of SLR and tidal flooding (Figure 5 c). For example, Keys and Mulder (2020)
983 analyzed home sales in Florida’s coastal areas from 2001 to 2020, excluding tracts af-
984 fected by major hurricanes to isolate the effects of SLR. The number of sales in high-
985 exposure areas began declining in 2013, dropping 16–20% relative to low-exposure ar-
986 eas by 2018. Home prices remained stable until 2016 but then fell 5–10% below trend
987 by 2020. This lead-lag pattern, where sales decline before prices, resembles trends ob-
988 served in the 2008 housing recession. The study attributed these shifts primarily to re-
989 duced demand in high-SLR areas, likely due to growing climate risk awareness among
990 buyers. Other studies on SLR report similar findings. Keenan et al. (2018) and McAlpine
991 and Porter (2018) examined the relationship between housing prices and exposure to SLR
992 in Miami-Dade County, Florida. Keenan et al. (2018) found that properties at higher
993 elevations appreciated more over time than similar properties in low-lying areas, even
994 after controlling for housing characteristics and location. This trend suggests that tidal
995 flooding may influence homebuyer preferences, reducing demand for properties more ex-
996 posed to SLR. McAlpine and Porter (2018) analyzed the relationship between housing
997 prices and tidal flooding, controlling for proximity to the shore. They found that prop-
998 erties with greater exposure to tidal flooding appreciated, on average, \$3 less per square
999 foot per year than those in lower-risk areas. This effect applies to both houses that are
1000 directly flooded and to homes near frequently flooded roads, indicating that broader in-
1001 frastructure disruptions also influence property values. Lastly, Bernstein et al. (2019)
1002 examined housing prices in coastal areas across the US, focusing on properties within
1003 400 meters of the shore. They found that homes exposed to SLR sell for about 7% less
1004 than comparable unexposed properties at the same distance from the beach. Since they
1005 found no correlation between SLR exposure and rental rates, this discount likely reflects
1006 homebuyers’ long-term concerns about future sea levels.

1007 Despite observed price differentials, the literature suggests that expected future losses
1008 in flood-exposed areas in the US are still not fully reflected in housing prices. Gourevitch
1009 et al. (2023) compared current housing prices in flood-prone areas with their fundamen-
1010 tal values, which account for expected flood damages and insurance costs. They estimated
1011 total overvaluation in flood-exposed areas at \$121–\$237 billion, depending on the assumed
1012 appreciation rate. This overvaluation increases the risk of a housing bubble, which, if
1013 it bursts, could harm homeowners and destabilize the broader economy.

1014 In conclusion, the interaction between natural hazards and housing prices leads to
1015 three key outcomes. First, at a broad spatial scale, destructive hazards reduce housing
1016 supply, temporarily driving up prices for unaffected properties. Though these increases
1017 vanish once rebuilding is complete, they can have lasting effects by raising the average
1018 wealth of residents and potentially triggering gentrification. Second, at a more localized
1019 level, properties in high-exposure areas tend to be discounted relative to those in less ex-

1020 posed areas. After an intense hazard event or updated risk mapping, these discounts ap-
1021 pear suddenly but often fade over time, likely due to shifting risk perceptions. In con-
1022 trast, with chronic hazards like SLR and tidal flooding, price discounts in more exposed
1023 areas tend to persist and grow. These long-term discounts can have significant economic
1024 consequences. Gourevitch et al. (2023) highlight several risks associated with declining
1025 housing prices in hazard-prone areas. First, lower prices may attract low-income house-
1026 holds, concentrating vulnerable populations in areas where the hazard is more frequent
1027 and intense. Additionally, declining property values erode homeowners' equity and heighten
1028 community-wide social vulnerability, especially for households whose homes are their pri-
1029 mary financial asset. Falling prices can also raise mortgage default risks. If property val-
1030 ues drop below mortgage balances, homeowners may be more likely to default, poten-
1031 tially destabilizing local housing markets. If prices fall below construction costs, rebuild-
1032 ing after a disaster may become financially unfeasible, leading to prolonged blight and
1033 non-recovery. Finally, declining property values reduce local tax revenues, limiting fund-
1034 ing for hazard adaptation and community resilience efforts.

1035 5 Mathematical Modeling of Post-Hazard Recovery and Long-Term 1036 Changes

1037 Here, we review simulation-based models that examine the impacts of natural haz-
1038 ards on long-term relocation. We classify the models into three categories based on their
1039 primary focus and methodological approach (Figure 6). The first category includes mod-
1040 els that simulate recovery following a single destructive event, while accounting for per-
1041 manent out-relocation of current residents. These models integrate engineering-based
1042 damage assessments with socio-economic factors influencing relocation decisions, such
1043 as place attachment and households' financial capacity. Their primary objective is to es-
1044 timate which residents are more likely to permanently out-relocate during the recovery
1045 process. The second category consists of models that simulate longer time frames and
1046 recurring hazards. These models incorporate behavioral economics to simulate flows of
1047 residents into, out of, and within communities, accounting for risk perception, hetero-
1048 geneous preferences, and financial constraints. Their main goal is to assess long-term de-
1049 mographic and economic changes in hazard-exposed communities, such as changes in pop-
1050 ulation size and economic segregation. The third category comprises models that sim-
1051 ulate relocation flows across multiple locations, such as all counties in the United States.
1052 These models build on ongoing relocation patterns and estimate how slow-onset hazards,
1053 such as SLR, could alter these trends over time.

1054 Before describing in detail models of hazard-induced relocation, we briefly overview
1055 models that focus on post-hazard recovery, which simulate how communities restore in-
1056 frastructure, housing, and services after a disruptive event. As discussed in earlier sec-
1057 tions, the recovery process can shape long-term relocation patterns. Therefore, even though
1058 these models do not explicitly simulate relocation, they remain relevant to this review.
1059 Most models on recovery build on engineering techniques and the disaster risk analysis
1060 literature (Cheng et al., 2024; Ceferino et al., 2018; Arora & Ceferino, 2023; Negri et al.,
1061 n.d.; Houg & Ceferino, 2025; Xu & Noh, 2021). Miles et al. (2019) classified recovery
1062 models into three categories: lifeline restoration, housing reconstruction, and community-
1063 wide recovery. They also identified various modeling approaches, including system dy-
1064 namics, agent-based modeling, and network models. For example, infrastructure-focused
1065 models simulate the restoration of essential services such as hospitals, transportation and
1066 utilities (Alisjahbana et al., 2023; Ramachandran et al., 2015; Davidson et al., 2017). Sim-
1067 ilarly, housing recovery models use Markov chains and agent-based approaches to pre-
1068 dict rebuilding timelines and neighborhood recovery patterns (Dhulipala et al., 2021; Ne-
1069 jat & Damnjanovic, 2012). At the community level, models such as ResilUS (Miles &
1070 Chang, 2011) integrate multiple recovery sectors, illustrating how interdependencies be-
1071 tween households, businesses, and infrastructure can shape recovery trajectories. Addi-

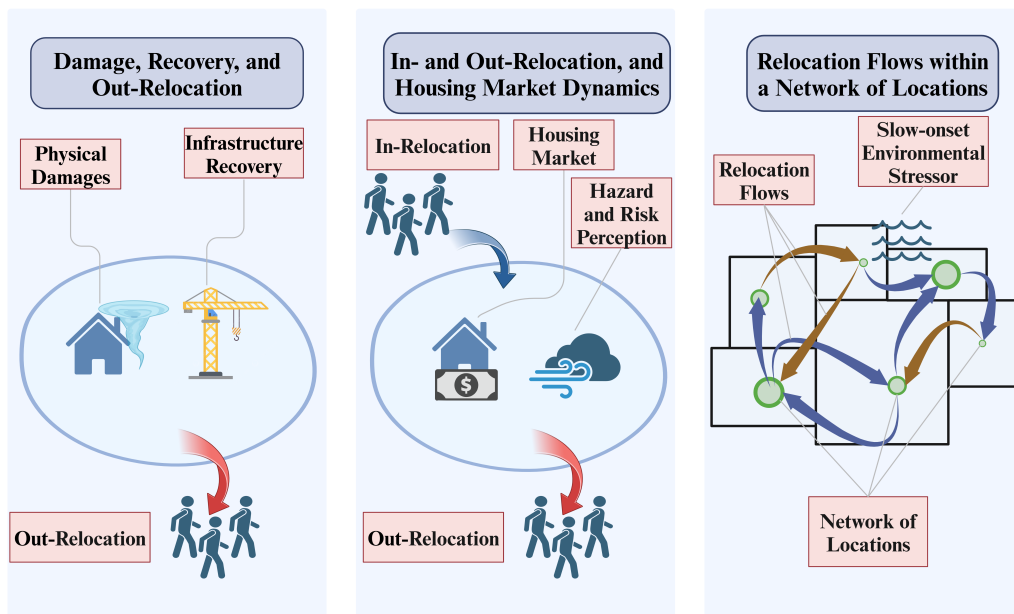


Figure 6. Schematic representation of the three categories of simulation-based models on hazard-induced relocation. The figure highlights the primary aspects each category emphasizes, including physical damage and recovery with out-relocation (Category 1), economic drivers of in- and out-relocation (Category 2), and large-scale relocation flows shaped by slow-onset hazards (Category 3). Created in BioRender. Malakun, A. (2025) <https://BioRender.com/1z4sd7q>

1072 tionally, Sutley and Hamideh (2020) introduced a fourth dimension—household recovery—
1073 modeling transitions of households through different housing stages, such as emergency
1074 shelter, temporary shelter, temporary housing, and permanent housing. These models
1075 provide valuable insights into the pace and extent of recovery, which can influence both
1076 in- and out-relocation.

1077 **5.1 Models on Recovery and Permanent Out-Relocation**

1078 Paul et al. (2024) reviewed models that examine permanent out-relocation induced
1079 by natural hazards. They classified each model based on the out-relocation drivers they
1080 consider, such as the extent of housing damage, place attachment, and socio-demographic
1081 characteristics. Most models use an agent-based approach to simulate household deci-
1082 sions following a destructive natural hazard. For example, Costa et al. (2022) developed
1083 an agent-based model to simulate homeowners’ decisions to either repair their damaged
1084 dwelling or permanently out-relocate after a major earthquake in San Francisco. Their
1085 model considers three factors influencing this decision: place attachment, the time re-
1086 quired to initiate repairs, and the financial extent of damages. The study found that place
1087 attachment, quantified using US Census Bureau surveys on neighborhood and home sat-
1088 isfaction, plays a significant role in decision-making, and that excluding this factor may
1089 significantly underestimate out-relocation. Other studies extend these models beyond
1090 homeowners to include out-relocation decisions of renters (Mongold et al., 2021; H. Bur-
1091 ton et al., 2019). Bhattacharya and Kato (2021) included in their model the effects of
1092 community characteristics (e.g., presence of essential services and economic opportuni-
1093 ties) and post-hazard policies on permanent out-relocation decisions. All these models
1094 primarily focus on the out-relocation of current residents after a destructive hazard event.
1095 They provide valuable insights into which households are more likely to permanently re-
1096 locate and which communities face higher risks of disruption. However, as discussed in
1097 previous sections, natural hazards can drive both out- and in-relocation, meaning these
1098 models cannot fully predict long-term, net population changes.

1099 **5.2 Models on Socio-Economic and Demographic Changes**

1100 Most of these models simulate hazard-exposed communities over multiple decades,
1101 capturing the effects of recurring extreme events, such as storm surge flooding, or grad-
1102 ual environmental changes, such as SLR. They employ agent-based modeling to exam-
1103 ine long-term socio-economic changes within these communities. Researchers use these
1104 models to explain empirical observations, such as temporary declines in housing prices
1105 after major disasters, and to project future outcomes like economic segregation. Most
1106 reviewed models in this category focus on flooding, which is spatially more predictable
1107 than other hazards. In flood-prone areas, households can be located either inside or out-
1108 side a floodplain while remaining within the same commuting zone. This spatial predictabil-
1109 ity influences local dynamics between exposed and non-exposed areas, which are reflected
1110 in housing market trends. For instance, studies show that after a flood, houses within
1111 the floodplain tend to appreciate less than comparable houses just outside it. A group
1112 of models simulates socio-economic shifts in flood-prone areas by focusing on the hous-
1113 ing market. They simulate the behavior of home buyers and sellers, with agents driven
1114 by their preferences (e.g., proximity to water and risk perception) and constraints (like
1115 income and budget). The hazard impacts the market by increasing perceived future losses
1116 and the financial burden from property taxes and insurance premiums. For example, Bakkensen
1117 and Barrage (2022) and de Koning and Filatova (2020) developed agent-based models
1118 to simulate flood-exposed housing markets. In these models, agents are attracted to coastal
1119 properties for the amenity of living close to water, but are also deterred by the perceived
1120 risk of future flood losses. Risk perceptions and preferences are heterogeneous across agents
1121 and evolve over time, with risk awareness increasing after a flood event. The models suc-
1122 cessfully reproduce observed depreciation of flood-exposed properties following a flood

1123 and the gradual price rebound as risk perception adjusts. They also show that even a
1124 small fraction of agents with overly optimistic expectations of future losses can artifi-
1125 cially inflate property values. These inflated values may then lead to sudden equity losses
1126 as the effects of SLR become more apparent and risk perception intensifies among a broader
1127 pool of prospective homebuyers. Additionally, they highlight the risk of economic seg-
1128 regation: as home prices drop below a certain threshold, less affluent households become
1129 unable to sell their homes, remaining trapped in hazard-exposed areas.

1130 McNamara et al. (2024) built on previous models (Brad Murray et al., 2013; Mc-
1131 Namara & Keeler, 2013) to investigate housing market dynamics in a coastal commu-
1132 nity exposed to SLR, focusing on the effects of community-level, in-place adaptation mea-
1133 sures such as beach nourishment. In their model, beach nourishment enhances the at-
1134 tractiveness of coastal properties, but it also increases property taxes, making homes less
1135 affordable. Additionally, SLR accelerates beach erosion, necessitating more frequent adap-
1136 tation efforts over time. The study explored various scenarios by adjusting government
1137 subsidies for beach nourishment and the price differences between coastal and inland prop-
1138 erties. They found that reduced government subsidies initially attract more affluent res-
1139 idents who can support nourishment efforts through higher property taxes. However, if
1140 inland property values also decline, the widespread depreciation leads to property ac-
1141 quisition by absentee landlords, resulting in an influx of low-income renters.

1142 Similarly, Karanci et al. (2016) and Karanci et al. (2018) presented an agent-based
1143 model simulating the interaction between housing market dynamics, community-level
1144 adaptation measures, and flood damage in a coastal town. Applied to Nags Head, North
1145 Carolina (US), the model runs over 50 years, incorporating recurring minor floods and
1146 a single major event at year 25. Results reveal a threshold effect: when the major event’s
1147 intensity remains below a critical level, the community recovers and resumes its prior
1148 growth trajectory. However, if the hazard intensity surpasses this threshold, a negative
1149 feedback loop emerges: flood damages lead to increased out-relocation, reducing prop-
1150 erty tax revenues and slowing adaptation efforts. This, in turn, heightens risk percep-
1151 tion and exacerbates future damages, reinforcing further out-relocation and stagnation.
1152 Similarly, Tonn and Guikema (2018) developed an agent-based model in which agents
1153 can collectively decide to implement seawalls protecting the entire community. They showed
1154 how reduced perceived risk can trigger the levee effect, attracting more residents to flood-
1155 prone areas and increasing their exposure to low-probability, high-impact events.

1156 Modeling the housing market to investigate socio-economic changes in hazard-exposed
1157 communities has also been applied to hazards beyond flooding. For example, Grinberger
1158 and Felsenstein (2016) developed an agent-based model to simulate the long-term wel-
1159 fare impacts of a hypothetical earthquake in Jerusalem, focusing on how physical dam-
1160 ages influence housing market dynamics and socio-economic inequalities. Their model
1161 shows how wealthier residents may gain a competitive advantage in the housing market
1162 after a destructive event, displacing low-income populations and leading to the gentri-
1163 fication of some neighborhoods. This model accounts for the effects of physical damage
1164 on reducing housing supply, but it does not explicitly simulate the reconstruction pro-
1165 cess.

1166 **5.3 Models on Relocation Networks**

1167 Models in this category simulate relocation patterns among a network of locations,
1168 such as all the counties composing the US. They estimate flows of migrants between lo-
1169 cations and analyze how slow-onset environmental stressors (e.g., SLR), influence on-
1170 going relocation trends. For example, Davis et al. (2018) and De Lellis et al. (2021) built
1171 on the radiation model (Simini et al., 2012; Boldini et al., 2024), a spatial interaction
1172 model that predicts relocation flows based on population distribution across locations.
1173 Davis et al. (2018) modified the standard radiation model by reducing the attractive-

1174 ness of flood-prone areas as destinations in the relocation network. De Lellis et al. (2021)
1175 introduced dynamic out-relocation rates that increase in locations affected by SLR. Both
1176 articles apply their models to case studies in Bangladesh, predicting cascading reloca-
1177 tion effects also in areas not directly affected by SLR. Robinson et al. (2020) took a dif-
1178 ferent approach, using machine learning to model relocation in the US. They trained two
1179 separate models: one based on historical IRS county-to-county relocation data, and an-
1180 other based on relocation patterns following Hurricanes Katrina and Rita (2005–2006
1181 IRS data). They then applied these models to simulate how future SLR could influence
1182 relocation patterns across the US. Their model predicts the intensification of existing re-
1183 location patterns towards urban areas, and indirect effects in receiving locations caused
1184 by population pressures.

1185 **5.4 Comparison of Different Models**

1186 We identify five key components of hazard-induced relocation that different mod-
1187 els incorporate to varying degrees: physical damage and recovery of infrastructure and
1188 services, permanent out-relocation of affected residents, in-relocation of new residents,
1189 behavioral economics and housing market dynamics, and relocation flows across a net-
1190 work of locations (Figure 6). Each model category emphasizes specific components while
1191 overlooking others. For example, models in the first category primarily simulate phys-
1192 ical damage and recovery, and incorporate factors influencing out-relocation, such as place
1193 attachment, but overlook in-relocation and housing market dynamics. Models in the sec-
1194 ond category simulate in- and out-relocation driven by economic considerations, often
1195 without explicitly modeling physical damage. Models in the third category consider both
1196 origins and destinations of relocation, but cannot incorporate household-level character-
1197 istics or building-specific damages without becoming computationally infeasible. These
1198 differences often reflect the disciplinary origins of the models. Models in the first cat-
1199 egory stem primarily from the engineering literature and build on research on hazard char-
1200 acteristics, physical damage assessment, and infrastructure recovery. Models in the sec-
1201 ond category originate from the economic literature and draw on studies of housing mar-
1202 ket dynamics, behavioral economics, and coupled human-natural systems. Models in the
1203 third category are refinements of the gravity model, which applies principles derived from
1204 physics to human relocation patterns.

1205 Integrating all components into a single model remains a significant challenge, but
1206 a more comprehensive approach is needed to better capture the complex interactions be-
1207 tween hazard impacts and relocation. Currently, no model fully integrates physical dam-
1208 age, recovery, out-relocation, in-relocation, and housing market dynamics. The only ex-
1209 ception is the model by Karanci et al. (2016), which attempts to incorporate all these
1210 aspects. However, this model relies on strong assumptions about how housing demand
1211 evolves over time, particularly in relation to in-relocation of new residents. Modeling in-
1212 relocation is especially challenging, as its relationship with natural hazards is complex
1213 and remains under-explored. Another important gap is the role of social connections in
1214 relocation decisions. As previously discussed, strong social ties—such as relationships
1215 with family, neighbors, and community organizations—can reduce the likelihood of per-
1216 manent out-relocation. Despite their recognized importance, none of the reviewed mod-
1217 els account for this factor, highlighting an opportunity for future research.

1218 **6 Conclusions**

1219 In this literature review, we examined the effects of natural hazards on human com-
1220 munities, with a specific focus on permanent relocation patterns. We addressed two key
1221 questions: (1) what factors influence relocation patterns in hazard-exposed communi-
1222 ties, and (2) what are the effects of relocation on the socio-economic and demographic
1223 characteristics of these communities. To answer these questions, we reviewed three types

1224 of studies: theoretical frameworks that explain the mechanisms driving relocation, em-
1225 pirical analyses that identify patterns and trends using data, and simulation-based mod-
1226 els that explore the dynamics of relocation and community change through mathemat-
1227 ical simulations. We kept our focus mostly on developed economies, particularly non-
1228 agriculture-dependent communities, as covering both developed and developing economies
1229 in depth would have made our review too broad.

1230 In addressing the first question, we found that the effects of natural hazards on re-
1231 location patterns are influenced by a combination of multiple factors, encompassing house-
1232 hold and community characteristics, and policies and government interventions. House-
1233 hold characteristics include wealth, risk perception, and place attachment, while com-
1234 munity characteristics encompass the availability of jobs, essential services, and social
1235 networks. Policies and government intervention include the implementation of in-place
1236 hazard adaptation measures and post-event financial stimuli. The interactions between
1237 natural hazards and these factors can be complex, sometimes triggering cascading effects
1238 within communities. For instance, a severe hazard event may displace a large number
1239 of residents, reducing the demand for essential services like schools and grocery stores.
1240 The closure of these services can discourage displaced residents from returning and prompt
1241 additional out-relocation, creating a self-reinforcing cycle of population loss and com-
1242 munity decline. In some cases, the very characteristics that attract in-relocation also in-
1243 crease a community's exposure to natural hazards. For example, forests provide natu-
1244 ral amenities in wildland-urban interface areas but also heighten wildfire risk, while prox-
1245 imity to waterfronts attracts residents despite the threat of flooding. In such contexts,
1246 the same factor can simultaneously draw new residents seeking environmental benefits
1247 and drive others out to avoid risk.

1248 In-place adaptation measures can also influence relocation outcomes. For instance,
1249 when building codes require costly adaptations, such as home elevation in flood-prone
1250 areas, some homeowners may be forced to out-relocate due to financial constraints. Con-
1251 versely, measures like seawalls can reduce perceived risk, attracting new residents to hazard-
1252 exposed areas and increasing exposure to rare, high-impact events that exceed the de-
1253 sign limits of these protections. Hazards characteristics, such as intensity, frequency, and
1254 spatial predictability, also shape relocation patterns. For example, more spatially pre-
1255 dictable hazards, like coastal flooding (e.g., delimited through flood zones), can lead to
1256 uneven relocation patterns within the same commuting zone, with high-exposure areas
1257 experiencing slower growth compared to less exposed ones. In contrast, hazards with low
1258 spatial predictability, such as tornadoes, do not exhibit such patterns. Given the com-
1259 plex interactions between natural hazards and other factors, we cannot accept the sim-
1260 plistic hypothesis that exposure to natural hazards automatically causes permanent out-
1261 relocation. Instead, communities with different socio-economic, environmental, and in-
1262 stitutional characteristics can experience vastly different relocation outcomes, even when
1263 exposed to the same hazard.

1264 In addressing the second question, we found that socio-economic and demographic
1265 changes in hazard-exposed communities result from the combined effects of in- and out-
1266 relocation. The reviewed literature highlights two key dimensions of these changes: shifts
1267 in population size due to net relocation and alterations in the socio-economic compo-
1268 sition of the resident population. The literature documents mixed findings regarding changes
1269 in population size. Some studies have attempted to correlate the frequency and inten-
1270 sity of natural hazards with population trends across large geographic scales, such as the
1271 entire US. These broad statistical analyses suggest that natural hazards generally do not
1272 disrupt pre-existing population trends. For example, analyses of US counties indicate
1273 that population changes are largely driven by trends from the preceding decade, with
1274 natural hazards showing no statistically significant effect. A notable case aligning with
1275 this conclusion is New Orleans, where the population had been declining steadily for four
1276 decades before Hurricane Katrina. Although the city regained a portion of its displaced

1277 population post-disaster, it eventually returned to its pre-hurricane downward trajec-
1278 tory. However, such large-scale studies have limitations: they often do not distinguish
1279 between different hazard types, which can produce varying effects. Moreover, they rely
1280 on coarse geographic units that may hide more localized mobility patterns. For instance,
1281 analyses at the census tract level revealed that tracts exposed to coastal flooding tend
1282 to experience slower growth compared to less exposed tracts within the same commut-
1283 ing zone. Moreover, while large-scale studies often downplay the impact of natural haz-
1284 ards on population trends, more focused research on specific hazards, such as SLR, re-
1285 veals different patterns. In the case of SLR, the gradual loss of land seems to have a greater
1286 long-term impact on population size than rare, high-intensity events. The literature par-
1287 ticularly highlights the risk of complete community abandonment in island communi-
1288 ties, where residents have limited or no options to retreat inland.

1289 Beyond changes in population size, natural hazards can also lead to significant socio-
1290 economic shifts within affected communities. The literature describes two contrasting
1291 outcomes. In some cases, destruction from intense hazard events displaces less affluent
1292 residents, creating opportunities for wealthier individuals to move in. This pattern was
1293 observed in several New Orleans neighborhoods after Hurricane Katrina, where new res-
1294 idents in heavily damaged areas were more affluent and better educated than those they
1295 replaced. In other cases, natural hazards exacerbate existing poverty, trapping vulner-
1296 able residents in high-risk areas as property values decline and relocation becomes finan-
1297 cially unfeasible. The likelihood of one outcome over the other often depends on the com-
1298 munity's overall attractiveness. In communities with desirable characteristics, such as
1299 access to jobs or natural amenities, hazards may accelerate gentrification by displacing
1300 vulnerable populations and attracting wealthier newcomers. Conversely, in communi-
1301 ties already facing stagnation or decline, natural hazards can deepen existing vulnera-
1302 bilities. In some cases, even in communities previously facing decline, post-hazard eco-
1303 nomic stimuli are leveraged by local stakeholders to promote development, increase at-
1304 tractiveness, and create incentives for gentrification.

1305 These socio-economic changes are often reflected in housing market dynamics. Nat-
1306 ural hazards can abruptly reduce housing supply, driving up prices across affected com-
1307 munities. Rising prices may enable wealthier homebuyers to dominate the market, con-
1308 tributing to gentrification in some neighborhoods. However, when comparing areas more
1309 or less exposed within the same community, studies often found that more exposed ar-
1310 eas experience a relative decline in property values, especially after severe events or up-
1311 dates to risk maps. This price decline can attract lower-income households, leading to
1312 a concentration of vulnerable populations in high-exposure zones. In the case of chronic
1313 hazards, such as SLR and tidal flooding, empirical observations found a persistent and
1314 growing price discount for properties with higher exposure. Yet, despite these localized
1315 price drops, properties in flood-prone areas across the US remain, on average, overval-
1316 ued, as future annual expected losses are not fully reflected in current market prices. This
1317 overvaluation raises concerns about potential housing market bubbles, which, in case of
1318 burst, could erode household wealth on a large scale and destabilize the broader econ-
1319 omy.

1320 Lastly, we reviewed simulation-based models that explore the effects of natural haz-
1321 ards on human communities. As discussed earlier, these effects are shaped by a complex
1322 interplay of individual behaviors and broader community characteristics. Given this com-
1323 plexity, developing comprehensive models that account for all relevant factors is chal-
1324 lenging. As a result, existing models typically focus on specific subsets of factors, address-
1325 ing particular aspects of hazard-induced relocation and socio-economic change. We clas-
1326 sified the reviewed models into three categories based on their primary focus. Models
1327 in the first category focus on physical damages and infrastructure recovery, and simu-
1328 late permanent out-relocation of certain households based on characteristics like place
1329 attachment and wealth. The second category focuses on socio-economic changes, sim-

1330 ulating both in- and out-relocation, and housing market dynamics. Finally, the third cat-
1331 egory consists of relocation models that simulate flows of residents between origin and
1332 destination areas, incorporating the effects of slow-onset environmental drivers such as
1333 SLR.

1334 These models serve various purposes. Some are used to validate assumptions about
1335 empirically observed phenomena. For example, some models have demonstrated how dif-
1336 ferences in risk perception and preferences for coastal living can explain the overvalu-
1337 ation of coastal properties relative to their fundamental risk-adjusted value. Other mod-
1338 els are employed to predict future outcomes, such as identifying neighborhoods that are
1339 most at risk of permanent out-relocation based on resident characteristics and hazard
1340 exposure. Most of the reviewed models incorporate stochastic components to account
1341 for the inherent uncertainties in predicting natural hazards and human behavior. Agent-
1342 based modeling is the most common approach, as it starts from diverse individual be-
1343 haviors to investigate aggregate-level outcomes. For instance, agent-based models are
1344 particularly effective in studying housing market dynamics, where heterogeneous, indi-
1345 vidual preferences of homebuyers and sellers shape broader socio-economic trends.

1346 Lastly, we identified research gaps in the existing literature and propose avenues
1347 for future investigation. First, more studies should examine socio-economic and demo-
1348 graphic changes in hazard-exposed communities, focusing on the long term (one to two
1349 decades) and using finer geographic units. Our review shows that if geographic units are
1350 too coarse certain localized effects remain undetected. For instance, in the US, Census
1351 tracts appear to capture localized trends that are not observable at the county level. Be-
1352 yond geographic scale, future studies should also differentiate between hazard types. We
1353 showed that different hazards—such as tornadoes, storm surges, and tidal flooding—can
1354 produce disparate relocation outcomes, and treating them as a single category may con-
1355 found the results. For example, in areas exposed to spatially predictable hazards like coastal
1356 flooding, residents can reduce their exposure by relocating a short distance, an option
1357 not available for less predictable hazards like tornadoes. Future analysis should also ex-
1358 pand the range of independent and control variables. For example, reviewed studies ex-
1359 amined whether pre-event population trends, population density, or the presence of schools
1360 influenced post-event population trends across similarly impacted communities. Build-
1361 ing on this approach, future research could assess the role of additional factors, such as
1362 presence of grocery stores, job opportunities, industry composition, and socio-economic
1363 indicators like unemployment levels. Moreover, beyond population size, future research
1364 should further examine socio-economic shifts in hazard-exposed communities, including
1365 changes in income, age distribution, and education. Despite their role in shaping gen-
1366 tification and economic segregation, these factors remain underexplored.

1367 Second, most studies focus on destructive events, while chronic, low-intensity haz-
1368 ards remain understudied. For example, tidal flooding is becoming more frequent due
1369 to SLR, yet little research examines how it affects long-term socio-economic and demo-
1370 graphic trends. One relevant question could be whether Census tracts exposed to tidal
1371 flooding are attracting lower-income households, leading to poverty traps. As sea lev-
1372 els continue to rise, understanding these patterns will become more and more important
1373 for developing effective adaptation strategies. Emerging evidence suggests that proper-
1374 ties in areas exposed to tidal flooding are already losing value. Some studies warn that
1375 values could decline even more abruptly in the future, leading to sudden wealth losses,
1376 trapping homeowners, and deepening economic and social vulnerabilities.

1377 Third, more household-level research is needed to understand relocation decision-
1378 making. Existing studies have identified several factors influencing out-relocation after
1379 a destructive event, but their relative importance remains unclear. For example, social
1380 networks—such as ties to family, friends, and communities—are often mentioned as key
1381 factors influencing relocation, yet few studies have attempted to quantify their impact
1382 on relocation decisions. Additionally, research has largely focused on those who leave hazard-

1383 exposed areas, while little is known about those who move in. The motivations and char-
1384 acteristics of residents relocating into hazard-exposed areas remain unexamined, despite
1385 their potential impact on housing markets and community resilience. For example, stud-
1386 ies suggest that people’s risk perception is strongly shaped by prior hazard experience.
1387 If new residents lack such experience, they may underestimate risks, leading to distorted
1388 housing prices, increased development, and lower preparedness in high-exposure areas.
1389 This, in turn, could raise long-term costs for governments tasked with disaster recovery.

1390 Lastly, future research should enhance simulation-based models to better capture
1391 the complex interactions between natural hazards and relocation patterns. Existing mod-
1392 els focus on distinct aspects of hazard-induced relocation, such as physical damage and
1393 infrastructure recovery, out-relocation, in-relocation, housing market dynamics, and re-
1394 location flows across regions. However, no model integrates all these components. In-
1395 tegrating physical damage, recovery, in- and out-relocation, and housing market dynam-
1396 ics into a single model represents an interesting opportunity to advance the field. In do-
1397 ing so, the main challenge lies in modeling in-relocation, as the characteristics and mo-
1398 tivations of residents moving into hazard-exposed areas remain underexplored. Another
1399 opportunity for model improvement is incorporating social networks effects into house-
1400 holds’ relocation decisions. However, as for in-relocation, social network effects remain
1401 insufficiently studied and further empirical research is required to model them mathe-
1402 matically.

1403 Open Research Section

1404 The only dataset used in this study is the U.S. Census Bureau’s resident popula-
1405 tion data for Orleans Parish, LA, retrieved from the Federal Reserve Bank of St. Louis
1406 (FRED) (U.S. Census Bureau, n.d.). All other information is based on previously pub-
1407 lished sources cited in the text.

1408 Acknowledgments

1409 The authors acknowledge financial support from the National Science Foundation (Grants
1410 No. CMMI-2332144 and No. CMMI-2332145). They also thank Abigail Victoria Malakun
1411 for her assistance in preparing the figures, as part of her final research project in fulfill-
1412 ment of her Civil Engineering degree at UC Berkeley.

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