Project Report

Should I stay or should I go? Leveraging data-driven approaches to explore the effect of various disaster policies on post-earthquake household relocation decision-making

EEFIT Research Grant Scheme 2022

The Institution of Structural Engineers

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October 29, 2024

Abstract

Devastating earthquakes can cause affected households to relocate. Post-earthquake relocation disrupts impacted households' social ties and, in some instances, their access to affordable services. Simulation-based approaches that model post-earthquake relocation decision-making can be valuable tools for supporting the development of related disaster risk reduction policies. Yet, existing versions of these models focus particularly on housing-related factors, which are not the sole driver of post-earthquake relocation. We integrate data-driven approaches and local perspectives to account for post-earthquake household relocation decision-making within an existing simulation-based framework for policy-related risk-sensitive decision support on future urban development. We use household survey data related to the 2015 Gorkha earthquakes in Nepal to develop a random forest model that estimates post-earthquake relocation inclination of disaster-affected households. The developed model holistically captures various context-specific factors important to the post-earthquake household relocation decision-making. We leverage the framework to quantitatively assess the effectiveness of various disaster risk reduction policies in reducing positive post-earthquake relocation inclination, with an explicit focus on low-income households. We demonstrate it using a future "Tomorrowville", a hypothetical expanding urban extent that reflects important social and physical characteristics of Kathmandu, Nepal. Our analyses suggest that the provision of livelihood assistance funds is more successful when it comes to mitigating positive post-earthquake relocation inclination than hard policies focused on strengthening buildings (at least in the context of the examined case study). They also suggest viable pro-poor pathways for mitigating disaster impacts without the need to create potentially politically sensitive income-based restrictions on policy remits.

Keywords: post-earthquake household relocation; data-driven approaches; disaster risk reduction policies; risk-sensitive urban development; pro-poor

ACKNOWLEDGMENT

We acknowledge the support of Earthquake Engineering Field Investigation Team (EEFIT) and the Institution of Structural Engineers, through the 2022 EEFIT Research Grant Scheme.

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Chapter 1

Introduction

Moderate-to-large earthquake events can adversely impact vulnerable urban environments, often resulting in significant disruptions to social and economic activities. Affected households may subsequently decide to relocate (e.g., Binder et al., 2015), as observed following major past seismic events, e.g., the moment magnitude (M) 6.9 Loma Prieta, California, USA, earthquake (Schwab et al., 1998), the M8.0 Wenchuan, China, earthquake (Ge et al., 2010), and the M7.8 and M7.3 Gorkha, Nepal, earthquakes (Wilson et al., 2016; He et al., 2018). Post-disaster relocation often causes emotional instability, distress, depression, trauma and other psychological effects among those who relocate (Bier, 2017; Makwana, 2019; Kılıç et al., 2006). It also has long-lasting impacts on the social ties of relocated households and, in some instances, can deprive them of access to affordable housing, healthcare, education, and employment for years and even decades after relocation (Badri et al., 2006). Furthermore, earthquake disasters have historically led to disproportionate relocations of socioeconomically vulnerable households, e.g., female-headed households, the elderly, racial and ethnic minorities, and the urban poor (Bier, 2017; Myers et al., 2008; Hunter, 2005; Morrow-Jones and Morrow-Jones, 1991). Inequities are further exacerbated by the additional relocation-induced implications and vulnerabilities that result. Therefore, stakeholders (e.g., urban planners, recovery planners, and emergency response authorities) must devise strategic disaster risk reduction (DRR) policies for mitigating positive post-earthquake relocation decision-making.

Simulation-based modelling approaches that capture post-earthquake relocation decision-making are useful tools that complement empirical studies in supporting the design of such DRR policies (e.g., Costa and Baker, 2022; Moradi and Nejat, 2020). For instance, Miles and Chang (2011) developed the *ResilUS* computational model based on fragility models and Markov chains to simulate community-based post-disaster housing recovery. *ResilUS* models households' decisions to leave or stay accounting for factors predominantly related to housing reconstruction (e.g., the debt incurred by housing repairs and the availability of temporary housing until housing repairs are finished). Nejat and Damnjanovic (2012) proposed an agent-based model using game theory to predict homeowners' decision-making (i.e., stay and repair or sell and leave) based on their neighbourhood's average reconstruction value and the predicted future reconstruction value. Moradi and Nejat (2020) presented the *RecovUS* spatial agent-based model to simulate households' decision-making (e.g., stay and repair, stay and wait for repairs, sell and leave) accounting for various factors, e.g., income, race, education, residential building damage, financial assistance, restoration of community assets and infrastructure, and neighbours' repair progress. Households are assumed to stay and repair if they have abundant financial resources to cover repair costs. Costa et al. (2022a) proposed an agent-based model for assessing temporary displacement and permanent relocation decision-making of households that centres on aspects related to the immediate built environment, e.g., availability of water and electricity, neighbourhood conditions, housing repair progress, neighbours' decisions, and socioeconomic factors. Costa et al. (2022b) further integrated place attachment (classified as "low" if both neighbourhood and housing satisfaction are below a certain threshold) into assessing households' decisions to stay and repair or relocate. Low-income households, renters and those occupying old buildings were identified as most likely to have low place attachment and, therefore, most prone to relocation (at least within the context of the San Francisco, California, USA, case study considered).

Thus, most existing simulation-based models for post-earthquake household relocation decision-making focus mainly on housing-related factors, including but not limited to the duration and costs of housing repairs, whether or not the household can afford these costs, and the availability and affordability of temporary housing while their home is under repair. This means that the models either neglect or do not give adequate attention to alternative factors that can motivate or discourage households from relocating, e.g., earthquake-induced livelihood impact. Many of these models have not been validated with empirical data or are only partially calibrated using highly aggregated relocation patterns observed after past earthquake events (Miles and Chang, 2011; Nejat and Damnjanovic, 2012; Costa et al., 2022a,b). Therefore, further research is needed to improve the understanding and modelling of post-earthquake household relocation decision-making.

We aim to address this challenge using a data-driven modelling approach that integrates a holistic range of context-specific factors to estimate post-earthquake household relocation decision-making. Data-driven approaches (e.g., logistic regression, random forest, regression kriging) have been previously used in the literature to develop models for assessing (Nejat and Ghosh, 2016; Nejat et al., 2020; Loos et al., 2023; Rosenheim et al., 2021; Costa et al., 2022c) or identifying factors related to (Myers et al., 2008; Zhang and Peacock, 2009; Binder et al., 2015) households' post-disaster behaviours as well as to track business recovery (Costa and Baker, 2021) and to estimate post-earthquake damage (Loos et al., 2020). However, these studies either (1) did not explicitly focus on relocation; or (2) considered data at more aggregated resolution (i.e., neighbourhood- or county-level) than individual households; (3) predominantly centred on the aftermath of wind-hazard events (e.g., hurricane) rather than (potentially more devastating) earthquake disasters; and (4) developed models specifically targeted at high-income locations that may not reflect Global South contexts. The proposed data-driven model, which overcomes these limitations, is integrated into an existing framework for policy-related risk-sensitive decision support on future urban development (Wang et al., 2023). The resulting enhanced framework can then be used to quantify the effectiveness of various DRR policies in mitigating households' decisions to relocate after an earthquake, with an explicit focus on the extent to which low-income households are impacted. We use Nepali household survey data related to the 2015 $M7.8$ and $M7.3$ Gorkha earthquakes to develop the required data-driven model. We leverage the model to demonstrate the enhanced framework using the "Tomorrowville" virtual urban testbed, which closely reflects important physical and social characteristics of Kathmandu.

We structure this chapter as follows. We introduce the enhanced simulation-based framework in Chapter 2. We describe the **Data-driven Model** developed for the case study in Chapter 3, present the case study application in Chapter 4, and provide results in Chapter 5. Finally, we offer some concluding remarks in Chapter 6.

Chapter 2

Proposed simulation-based framework

We advance the existing framework proposed in Wang et al. (2023) to explicitly account for post-earthquake household relocation decision-making, as shown in Figure 2.1. The original Wang et al. (2023) framework leveraged the Tomorrow's Cities Decision Support Environment (Cremen et al., 2023) and facilitated the development of compulsory household-level financial soft policies (e.g., insurance, tax relief) for reducing disaster risk in expanding urban areas. The enhanced framework encompasses seven modules: (1) **Policy Bundles**; (2) **Urban Planning**; (3) **Local Perspectives**; (4) **Seismic Hazard**; (5) **Physical Infrastructure Impact**; (6) **Social Impact**; and (7) **Computed Impact Metrics**. (1), (2), (4), (5), (6), and (7) are modified versions of modules within the original framework. The characterisation of post-earthquake household relocation decision-making is facilitated by the new **Local Perspectives** module and its accompanying **Data-driven Model**.

Stakeholders first design disaster risk reduction (DRR) policies (in the **Policy Bundles** module) and apply these policies to a (conditional) urban plan associated with a specific time instance (in the **Urban Planning** module), both of which collectively produce a **Visioning Scenario**. A **Visioning Scenario** represents an urban system at a snapshot in time. While this could be the current version of the urban system, it is intended for the framework to be used in a forward-looking manner. The information stored in the **Visioning Scenario** and **Local Perspec-**

tives informs the calculations of modules (4) to (6), which collectively comprise the **Computational Model**. Modules (4) to (6) produce seismic hazard calculations, physical infrastructure impacts, and social impacts, respectively. The **Local Perspectives** module provides relevant context-specific information on household relocation decision-making. This information informs the development of a **Data-driven Model**, which is used within the **Social Impact** module to estimate whether households decide to relocate or stay. These estimations are then translated into a Poverty Bias Indicator (*PBI*), which measures the extent to which low-income households disproportionately decide in favour of relocation. Each iteration of the framework produces an assessment of impacts for one specific **Visioning Scenario**. The optimal **Visioning Scenario** is the one that produces the lowest *PBI*. We use Monte Carlo sampling to capture uncertainties within modules (4) to (6), in line with Cremen et al. (2022). Most modules introduced in Wang et al. (2023) are only briefly discussed. Described in detail are the newly introduced **Local Perspectives** module and the accompanying **Data-driven Model**, the enriched **Social Impact** module, and the **Computed Impact Metrics** that depend on the **Social Impact** module.

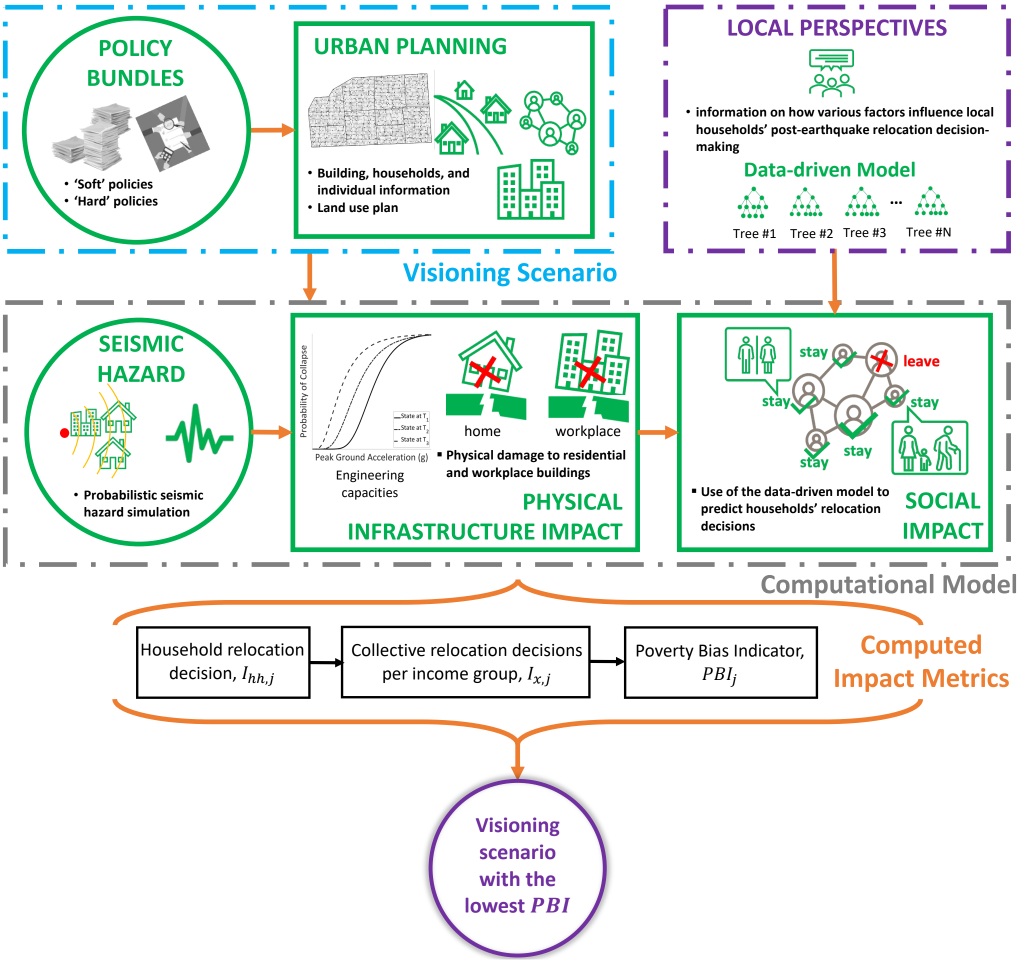

Figure 2.1: Simulation-based framework for quantitatively assessing the effectiveness of DRR policies in mitigating household decisions to relocate after an earthquake.

2.1 Brief Description of Some Modules in the Original Framework

The **Urban Planning** module contains an urban plan that provides detailed information on land use, buildings, households and individuals associated with a specific urban area at a prescribed time (possibly in the future, Menteşe et al., 2023). Within the context of the proposed enhanced framework, the **Policy Bundles** module encompasses one or more DRR policies that broadly aim at mitigating decisions to relocate after an earthquake. These policies could be 'soft' (e.g., post-earthquake livelihood assistance funds) as well as 'hard' (e.g., upgrading of existing infrastructure facilities to higher building codes). For this particular study, the **Seismic**

Hazard module stores the seismic source and rupture features of a specific earthquake event (scenario). It estimates the resulting ground-motion intensity measures (IMs) at the locations of exposed assets (e.g., buildings), i.e., ground-motion fields (GMFs). The **Physical Infrastructure Impact** module uses the GMF outputs from the **Seismic Hazard** module in combination with fragility models to estimate physical damage to buildings. This damage is represented as a discrete damage state (DS). The reader is referred to Sections 2.1 to 2.4 in Wang et al. (2023) for more details on these modules.

2.2 Local Perspectives

We integrate **Local Perspectives** to allow for context-specific people-centred characterisation of post-earthquake household relocation decision-making. The **Local Perspectives** module includes information (e.g., household relocation survey data, government reports, social media information) on how various local factors (e.g., socioeconomic features) relate to household relocation decisions. This knowledge is then used to calibrate a predictive **Data-driven Model** for relocation decision-making.

2.3 Data-driven model

The **Data-driven Model** estimates post-earthquake household relocation decisions. The post-earthquake relocation decision for the hh-th household in the j-th Monte Carlo sample, $I_{hh,j}$, is binary. $I_{hh,j} = 1$ means the hh-th household decides to relocate and $I_{hh,j} = 0$ indicates otherwise. It is developed by applying statistical learning methods (e.g., logistic regression, random forests) to the **Local Perspectives** data. The **Data-driven Model** is therefore inherently context-specific, enabling a more accurate characterisation of post-earthquake household relocation decision-making compared to generic, heuristic models.

2.4 Social Impact

The **Social Impact** module uses outputs from the **Physical Infrastructure Impact** module and leverages the **Data-driven Model** to capture the post-earthquake relocation decision-making of each household ($I_{hh,j}$), considering the policies that feature within the **Policy Bundles** module. This module further computes collective relocation decisions made by households across different income groups ($I_{x,j}$). $I_{x,j}$ for the j-th Monte Carlo sample is computed as:

$$I_{x,j} = \frac{\sum I_{hh,j,x}}{n_x} \quad (2.1)$$

where x refers to low- (low), middle- (mid), high- ($high$), or all- (all) income groups, $I_{hh,j,x}$ is the hhth household relocation decision associated with income group x, and n_x is the total number of households within income group x.

2.5 Computed Impact Metrics

The **Computed Impact Metrics** module translates the $I_{x,j}$ outputs from the **Social Impact** module into a single-valued PBI_j, which measures the extent to which low-income households disproportionately decide in favour of relocation. That is:

$$PBI_j = \frac{I_{low,j}}{I_{all,j}} - 1 \quad (2.2)$$

A negative value of PBI_j implies that the policies within the **Policy Bundles** module (and thus the associated **Visioning Scenario**) are pro-poor, i.e., the specific earthquake scenario considered does not result in a disproportionate number of decisions to relocate among low-income households. See Section 2.6 in Wang et al. (2023) for more details on PBI.

Chapter 3

A Data-driven Model

We demonstrate the **Local Perspectives** module by developing a **Data-driven Model** to characterise the relocation inclination of Nepali households after the 2015 $M7.8$ and $M7.3$ Gorkha earthquakes. The model estimates relocation inclination (i.e., willingness to relocate) as a proxy for a more definitive relocation decision, due to the constraints of the **Local Perspectives** dataset used (see Chapter 3.1). This dataset comprises household-level survey data related to the 2015 Gorkha earthquakes, which were collected in the 11 districts most affected by these events outside of the Kathmandu Valley. We note the model is developed specifically for households in Kathmandu, and should not be used outside this remit without further context-specific investigations (involving information on local perspectives). The **Data-driven Model** is a random forest model (Breiman, 2001). This type of model is suitable for estimating post-earthquake household relocation inclinations for two reasons: (1) it does not require any assumption to be made on the probability distributions of data; and (2) as a tree-based method, it can naturally handle both categorical and continuous data (Breiman, 2001). The model's outcome is the probability of each household having positive inclination to relocate. Details on the development of the data-driven model can be found in Wang et al. (2024).

3.1 Description of Local Perspectives data

The **Local Perspectives** data are derived from the results of the Independent Impacts and Recovery Monitoring (IRM) project, a longitudinal study conducted by

The Asia Foundation to systematically monitor disaster-induced social impacts, recovery patterns, and disaster-affected households' evolving needs after two devastating earthquakes struck Nepal in April ($M7.8$) and May ($M7.3$) 2015 (The Asia Foundation, 2019). The IRM project team revisited the same disaster-affected households and asked them similar questions over a five-year duration following the disaster (see Figure 3.1). Questions included, for instance, "to what extent was your livelihood affected by the earthquake?", "do you or anyone else in your household plan to migrate in the next 12 months?" (which captures household relocation inclination),"how satisfied are you with the electricity?", "approximately how much damage has the earthquake caused to your house?", "how much of the NPR 300,000 grant (from the National Reconstruction Authority) have you received at this point?", and "what is your household's source of income?"

In this study, we adopt the fourth-round survey data (collected in April 2017; The Asia Foundation, 2017) - as opposed to previous survey rounds conducted during the emergency response (The Asia Foundation, 2015) and the early recovery phase (The Asia Foundation, 2016a,b) when temporary displacement was the dominant migration pattern (The Asia Foundation, 2016b) - to focus on long-term household relocation inclination. We do not adopt the fifth-round survey data (collected between September and October 2019; The Asia Foundation, 2019) because any household relocation inclination observed at that point was not likely to be associated with the earthquakes in question given that "[t]he economy recovered in three years, 90% of people were back in their homes after four years, and . . . infrastructure and non-domestic constructions took five years to rebuild and repair" (Platt et al., 2020).

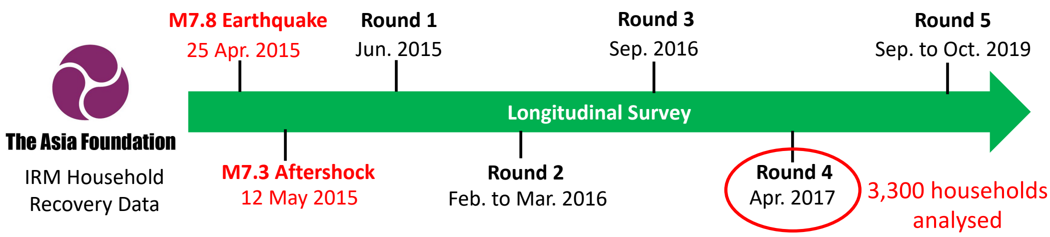

Figure 3.1: The timeline of the Independent Impacts and Recovery Monitoring (IRM) project, a five-year longitudinal study conducted by The Asia Foundation. IRM was designed to systematically monitor disaster-induced social impacts, recovery patterns, and disaster-affected households' evolving needs after two devastating earthquakes struck Nepal in April ($M7.8$) and May ($M7.8$) 2015. The fourth-round data, containing 3,300 complete responses, are used in this case study.

The fourth-round survey data include information on the respondent (e.g., age, income, gender, profession, broad ethnicity group, educational attainment) as well as their household-level characteristics (e.g., household size, annual household income). The survey data contain responses from 4,854 households. Excluding households with "unknown" residential damage or "unknown" status of access to government funding leads to a total of 3,300 complete responses (samples), which are used to develop the model. Among these responses, only 154 households are deemed to have had an inclination to relocate.

3.2 Selected Predictors

We first select a set of household-level predictors to include in the **Data-driven Model**, based on an extensive literature review of relocation following historical disruptive events (e.g., Myers et al., 2008; Peacock et al., 2014; Comerio, 2014; Badri et al., 2006; Fussell et al., 2010; Ge et al., 2010; Henry, 2013; He et al., 2018, etc.) including the 2015 Gorkha earthquakes, and broader studies on resilience and social vulnerability (e.g., Cutter et al., 2010, 2003, etc.).

The review identifies numerous factors influencing household relocation decision-making (and therefore likely to be related to relocation inclination). These factors vary in prominence across different contexts (Paul et al., 2023; Henry, 2013), highlighting the importance of using bespoke models for characterising household relocation decision-making. Paul et al. (2023) grouped these factors into four broad categories: housing matters, financial aspects, social and community aspects, and demographics. Housing matters include housing (residential) damage, housing type (e.g., single-family or multi-family), tenure time or hometown status (which is also used by Nejat and Ghosh, 2016, as a proxy for place attachment). Financial aspects include property damage losses, whether the property is insured, and availability of external financial assistance such as government aids, grants, and loans (Alisjahbana et al., 2022). Social and community aspects include family and relationships, livelihood, neighbourhood damage level, place satisfaction, etc. Demographics include housing tenure (i.e., renters or owners), income, age, gender, race and ethnicity, educational attainment, etc.

The eight predictors (see Figure 3.2) selected are residential damage, access to government funding (from the National Reconstruction Authority of Nepal), livelihood impact, place satisfaction, household income group, gender of the household head, age of the household head, and household size. Table 3.1 provides descriptions of these predictors and examples of literature that support their inclusion in the model.

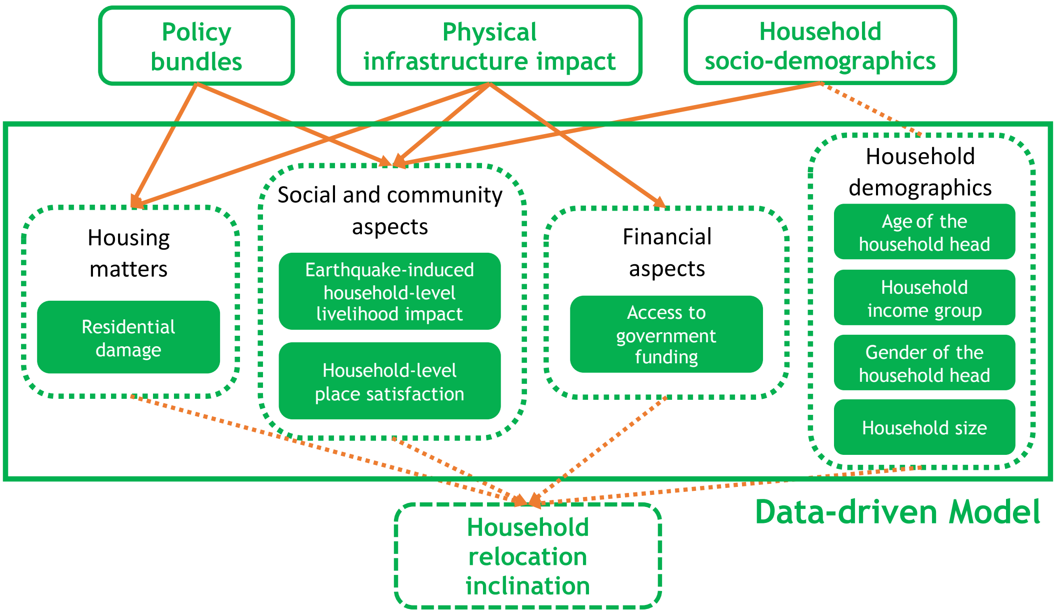

Figure 3.2: Schematic representation of the data-driven model developed in this case study for assessing post-earthquake relocation inclination of Nepali households. The data-driven model holistically integrates various household-level factors, i.e., residential damage, livelihood impact, place satisfaction, access to government funding, age of the household head, household income group, gender of the household head, and household size.

Table 3.1: Household-level predictors considered for inclusion in the case-study **Data-driven Model**. These predictors span the four categories of factors related to household relocation decision-making identified by Paul et al. (2023).

Category	Predictor	Description	Literature
Housing matters	Residential damage	Whether the residence was damaged by the earthquakes. Possible categorical values: 0 (not damaged) and 1 (damaged).	Costa et al. (2022a); Myers et al. (2008); Fussell et al. (2010); Peacock et al. (2014)
Financial aspects	Access to government funding	Whether the household has received a reconstruction grant from the National Reconstruction Authority of Nepal. Possible categorical values: 0 (not received) and 1 (received).	Comerio (2014); Alisjahbana et al. (2022); Kotani et al. (2020); Hamideh and Sen (2022)
Social and community aspects	Livelihood impact	Whether the livelihood of the household was impacted by the earthquakes. Possible categorical values: 0 (not impacted) and 1 (impacted).	Bolin and Bolton (1983); Wang et al. (2015); Henry (2013); Zhang and Peacock (2009); Cong et al. (2018); Comerio (2014); He et al. (2018)
	Place satisfaction	Whether the household is currently satisfied with its electricity and drinking water supply, schools, medical facilities, and roads. Possible categorical values: 0 (not satisfied) and 1 (satisfied).	Lu (1998); Tan (2016); Costa et al. (2022b); Speare (1974)
Household demographics	Household income group	Possible categorical values: 1 (monthly income lower than 20,000 Rs, i.e., low-income), 2 (monthly income between 20,000 and 40,000 Rs, i.e., middle-income), and 3 (monthly income above 40,000 Rs, i.e., high-income).	(Cutter et al., 2003; Myers et al., 2008; Morrow-Jones and Morrow-Jones, 1991; Ardayfio-Schandorf, 2012; Appeaning Addo, 2013; Addo, 2016)
	Gender of the household head	Possible categorical values: 1 (female) and 2 (male).	(Cutter et al., 2003; Myers et al., 2008; Morrow-Jones and Morrow-Jones, 1991)
	Age of the household head	Possible integer values: integers greater than 18.	Anton and Lawrence (2014); Nejat and Ghosh (2016); Clark et al. (2017); Speare (1974); Cutter et al. (2003)
	Household size	The number of individuals within the household. Possible integer values: positive integers.	(Cutter et al., 2003; Xu et al., 2017; Durage et al., 2014)

3.3 Data Derivation

The information required to characterise the predictors is then obtained from the IRM survey data. Positive relocation inclination is assigned to households that report at least one member currently planning to migrate in their responses to question D22. Residential damage is obtained from responses to question B1. Household size, gender of the household head, and age of the household head are obtained from responses to demographic questions (not numbered), assuming that the survey respondent is the household head. This assumption is justified, given that the survey respondent eligibility criteria stipulate that the respondent “plays an important role in the decision-making process in the family.” We assume the earthquakes impacted the livelihoods of households who indicated that their jobs were “completely affected” or “somewhat affected” (for question C2). Data on access to government funding is obtained from responses to question F14. For place satisfaction, we assume households who indicated for question E2 that they were “somewhat dissatisfied” or “dissatisfied” with electricity, water, schools, medical facilities, or motorable roads are not satisfied. Household income group information is obtained by merging the income brackets reported by respondents for question A9 as follows: a low-income household has a monthly income lower than 20,000 Rs, a middle-income household has a monthly income between 20,000 Rs and 40,000 Rs, whereas a high-income household has a monthly income above 40,000 Rs. These income groupings are determined based on the average monthly Nepali household income of 30,121 Rs (27,511 Rs for rural households and 32,336 Rs for urban households; Nepal in Data, 2018).

Chapter 4

Case-study description

We leverage the enhanced simulation-based framework to investigate the effect of different disaster policies on mitigating post-earthquake relocation inclination across households in the 11 districts most affected by the 2015 Gorkha earthquakes outside of the Kathmandu Valley, Nepal, using the **Data-driven Model** developed in Chapter 3. We adopt the Tomorrowville expanding virtual urban testbed as our case-study region (Menteşe et al., 2023), which was largely developed based on data from the Kathmandu Valley, recognising the effectiveness of virtual testbeds as neutral spaces for testing community resilience analysis tools (Amin Enderami et al., 2022).

4.1 Urban Planning

We use the TV50_total version of Tomorrowville, which includes 4,810 existing buildings in today's Tomorrowville (TV0) and 5,346 new buildings anticipated to be built in 50 years (TV50_b2) as a result of rapid urban expansion, shown in the left panel of Figure 4.1. TV50_total contains 8,713 residential buildings and 1,443 non-residential (e.g., commercial, industrial, agricultural, mix-use) buildings. These buildings consist of 11 construction types; new buildings to be built in TV50_b2 are, on average, much stronger and more ductile than existing buildings in TV0 (see Gentile et al., 2022; Wang et al., 2023, for more details). There are three types of residential polygons (low-, middle-, and high-income; see the left panel of Figure 4.1). Households within the same polygon all belong to the same income group. TV50_total includes 6,766, 3,059, and 7,985 low-income, middle-income, and high-income households, respectively. See Chapter 3.1 in Wang et al. (2023) for more details on TV50_total.

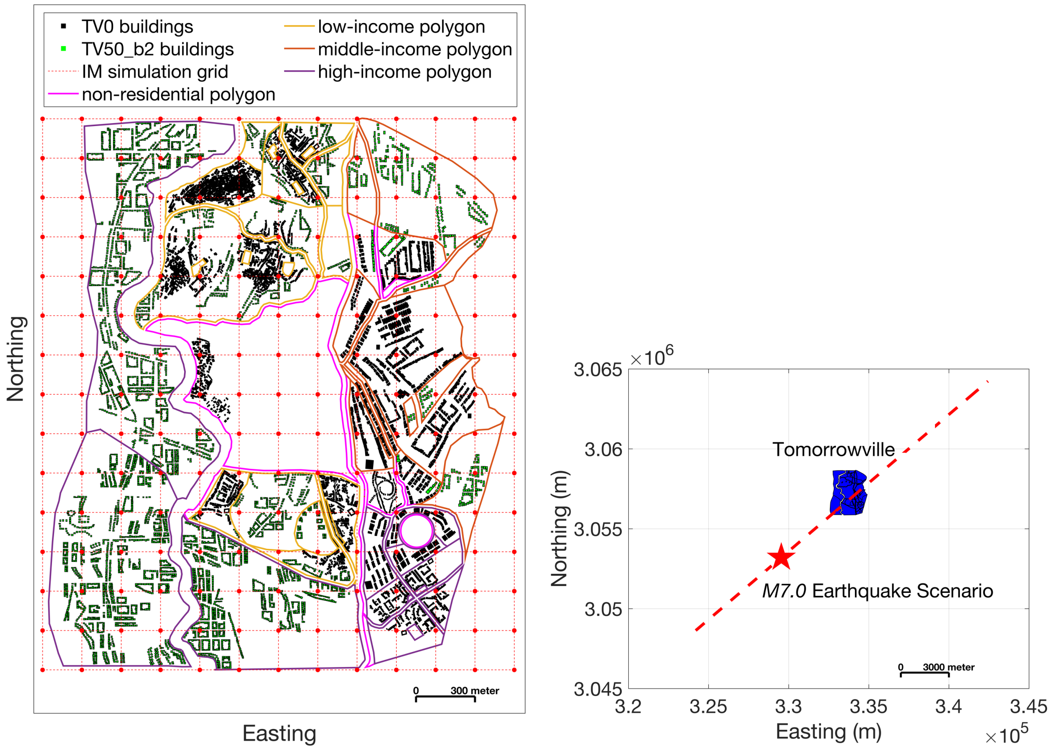

Figure 4.1: The left panel shows the buildings projected to be present in Tomorrowville in 50 years, as well as the associated land use polygons (TV50_total). TV50_total includes 8,713 residential buildings and 1,443 non-residential buildings. GMFs are simulated on a 200 m × 200 m grid (marked in red) across Tomorrowville polygons. The right panel shows the hypothetical *M*7.0 earthquake scenario considered for this case study. The underlying seismic source is a vertical strike-slip fault that ruptures 24 km, as shown in red.

4.2 Policy Bundles

We consider four DRR policies for mitigating post-earthquake household relocation inclination in TV50_total (see Table 4.1). Policy #1, which provides livelihood assistance funds to households in which at least one member is made unemployed by an earthquake event, is a 'soft' (and compensatory) policy. We assume that this policy eradicates the effect of livelihood impact on household relocation inclination. The other policies, which involve upgrading the most vulnerable TV0 residential buildings to higher building codes, are 'hard' (and corrective). Policy #3 is income-based (i.e., targets only low-income households) and is designed to explicitly facilitate pro-poor outcomes. Policies #2 and #3 demand intensive resources to improve the seismic vulnerability of 2,666 and 2,248 buildings, respectively. Note that relevant buildings that act as both workplaces and residences are upgraded under policies #2 and #3.

Table 4.1: Policies considered for this case study. 'RC' refers to reinforced concrete.

Policy	Type	Description
#1	Soft & compensatory	Provides livelihood assistance funds to households in which at least one member is made unemployed by an earthquake
#2	Hard & corrective	Replaces non-RC residential buildings (2,666 buildings in total) with high-code RC buildings
#3	Hard & corrective	Replaces non-RC low-income residential buildings (2,248 buildings in total) with high-code RC buildings

4.3 Seismic Hazard

We consider a fictitious $M7.0$ earthquake scenario on a hypothetical vertical strike-slip fault through Tomorrowville (shown on the right panel of Figure 4.1), given the synthetic nature of the case-study testbed. We use the ground-motion model in Campbell and Bozorgnia (2014) and the spatial and cross-IM (intensity measure) correlation model in Markhvida et al. (2018) to simulate spatial cross-correlated GMFs across a 200m $\times$ 200m grid of Tomorrowville (as shown on the left panel of Figure 4.1). We use Monte Carlo sampling to simulate 500 sets of GMFs for different IMs required by the considered fragility models (see Table 5 in Wang et al., 2023). Five hundred simulations are deemed appropriate, as this number produces stable social impact assessment results (see Chapter 5 for details). Ground-motion IM values for each building are taken to be those simulated at the nearest grid point.

4.4 Physical Infrastructure Impact

We use fragility models associated with each building type to compute the damage state (*DS*) of each building, conditional on the simulated IM values (outputs of the **Seismic Hazard** module). See Gentile et al. (2022) for details on the fragility models associated with Tomorrowville's buildings. The exact fragility models used are influenced by the three hard policies included in the **Policy Bundles** module.

The *DS* damage classification of the fragility models is translated to a binary residential damage classification to comply with the required input format of the **Data-Driven Model**. $DS = 0$ ("no damage") is mapped to *Residential damage* $= 0$, representing "not damaged". $DS = 1$ ("slight damage"), $DS = 2$ ("moderate damage"), $DS = 3$ ("extensive damage"), and $DS = 4$ ("complete damage") are mapped to *Residential damage* $= 1$, representing "damaged" (FEMA, 2022).

4.5 Social Impact

The **Social Impact** module uses information from the **Physical Infrastructure Impact** module (i.e., the *DS* of each building and the converted residential damage classification), the **Urban Planning** module (e.g., the workplace buildings where employed individuals work, the age and gender of the household head, household income group, and household size), and the **Policy Bundles** module (i.e., how constituent policies affect the earthquake-induced household-level livelihood impact and residential building *DS* of each household) to quantify earthquake-induced household-level livelihood impact and the availability of government funding.

We assume that workplace buildings with at least extensive damage ($DS \geq 3$) cannot function, so the livelihoods of individuals working in these buildings are impacted. A household's livelihood is deemed to be impacted if the livelihoods of one or more of its employed members are impacted. We assume households with complete or extensive damage ($DS \geq 3$) to their residences will be provided with government funding. This assumption is consistent with the eligibility criteria for the reconstruction grant by the National Reconstruction Authority of Nepal after the 2015 Gorkha earthquakes (International, 2017).

We randomly assign low place satisfaction to 40.7% high-income, 39.9% middle-income, and 34.6% low-income households, in line with the respective proportions of each income group associated with low place satisfaction in the household survey data used (see Chapter 3.1 for details). Note that the relatively higher place satisfaction of low-income households is consistent with observations in the literature. For example, Adriaanse (2007) found that low-income households are usually associated with low residential mobility (e.g., Ardayfio-Schandorf, 2012; Appeaning Addo, 2013). They build up habitual routines over time and become psychologically fused with their residences, thereby having positive place satisfaction (Addo, 2016).

This module finally leverages the **Data-driven Model** to compute the probability of having a positive relocation inclination for each TV50_total household across each GMF (i.e., Monte Carlo sample). We use a different random threshold value between 0 and 1 to translate this probability into a binary outcome ($I_{hh,j} = 0$ or $I_{hh,j} = 1$) for each Monte Carlo sample; $I_{hh,j} = 1$ is assigned if the probability exceeds the threshold value and vice versa.

Chapter 5

Results

Figure 5.1 displays the damage states (DSs) of Tomorrowville buildings averaged across the 500 sets of GMFs generated for the considered $M7.0$ earthquake scenario and four building portfolios: the original TV50_total building portfolio (top left panel) and two upgraded building portfolios associated with #2 (bottom left panel), and #3 (bottom right panel), respectively. The majority of buildings to be replaced under policy #2 are in the low-income polygons. This explains why the policy noticeably reduces the positive difference between the average DSs of buildings in the low-income polygons and those in the middle- and high-income polygons.

Figure 5.2 shows the reduction in the number of households with positive relocation inclinations under policies #1 to #3 (and no policy), averaged across the 500 sets of GMFs. Policy #1 (soft and compensatory) is the most effective in mitigating positive post-earthquake relocation inclination across all income groups. Policy #3, which is a subset of policy#2, leads to the smallest reduction in the number of households with positive relocation inclination.

Figure 5.3 shows for all policies (and no policy) the PBI_j averaged across the 500 sets of generated GMFs. All policies lead to some reduction in PBI_j. Policy #3 is overall the most pro-poor (i.e., it has the largest number of negative average PBI_j values) among those considered in this case study. This is expected given the low-income remit of policy #3. Policy #1, a soft and compensatory policy that does not differentiate based on income, is associated with an overall negative PBI_j, making it the second most pro-poor policy among those considered.

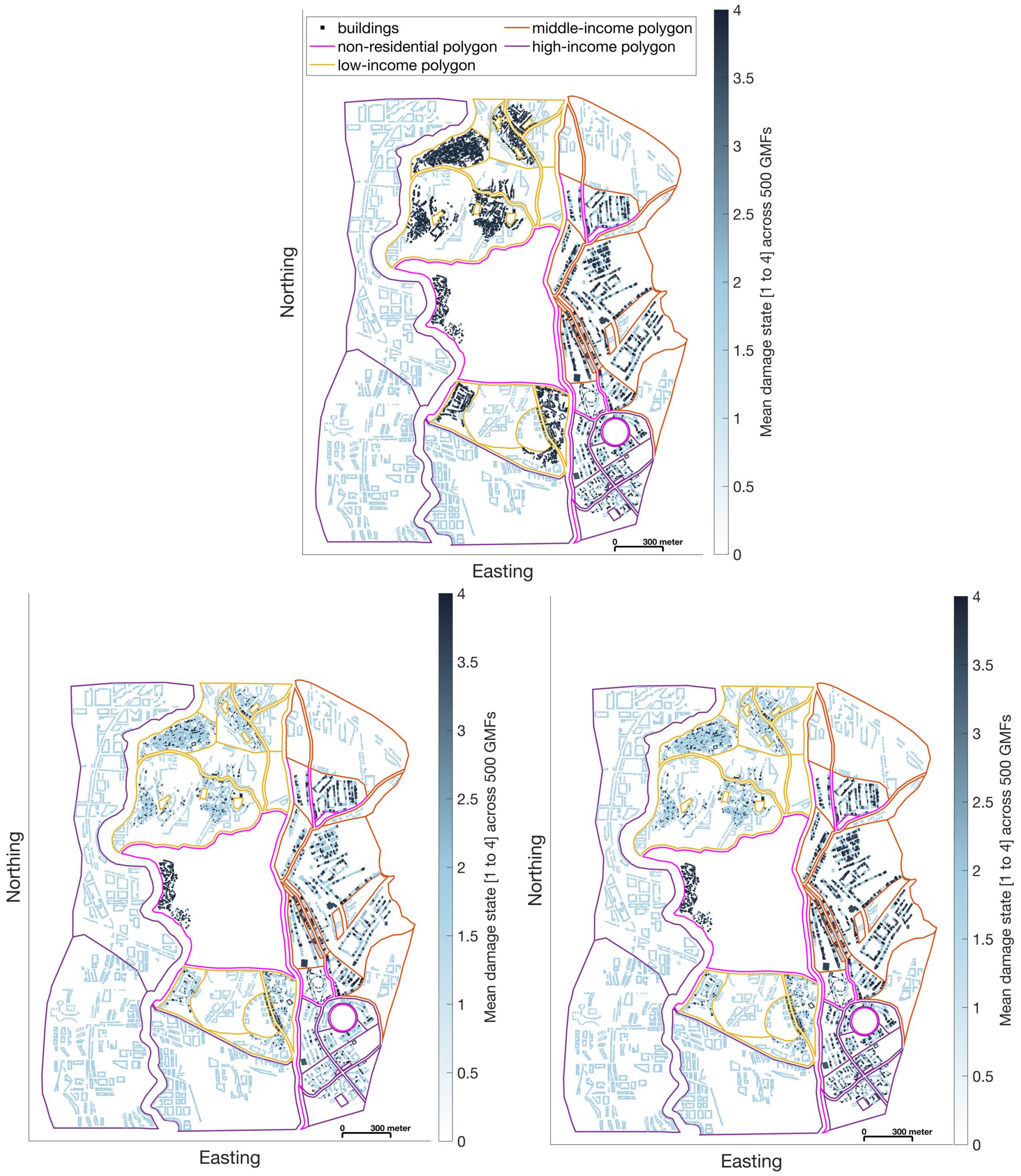

Figure 5.1: Average damage states DSs (0 = no damage, 1 = slight damage, 2 = moderate damage, 3 = extensive damage, 4 = complete damage) of TV50_total buildings across the 500 sets of GMFs generated for the considered M7.0 earthquake scenario. The top left panel shows the results for the original TV50_total building portfolio, and the bottom left panel and bottom right panel show the results for policies #2 and #3, respectively (see Chapter 4.2 for details).

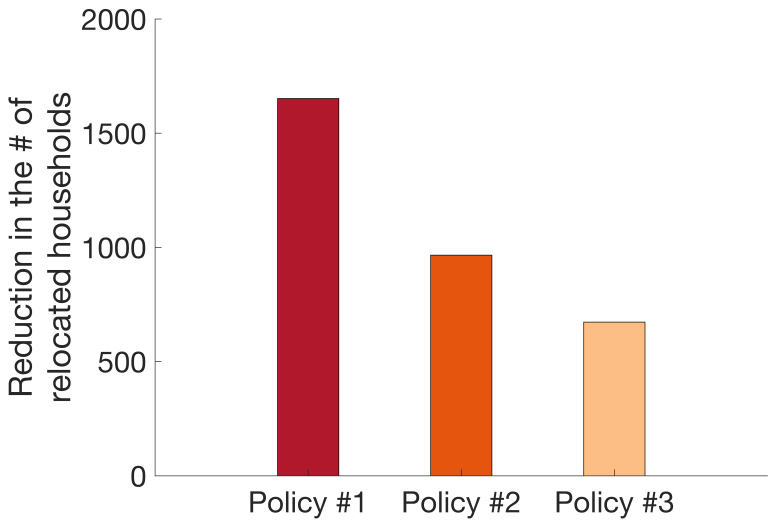

Figure 5.2: The reduction in the number of households with positive relocation inclinations under policies #1 to #3 (and no policy) averaged across the 500 generated sets of GMFs.

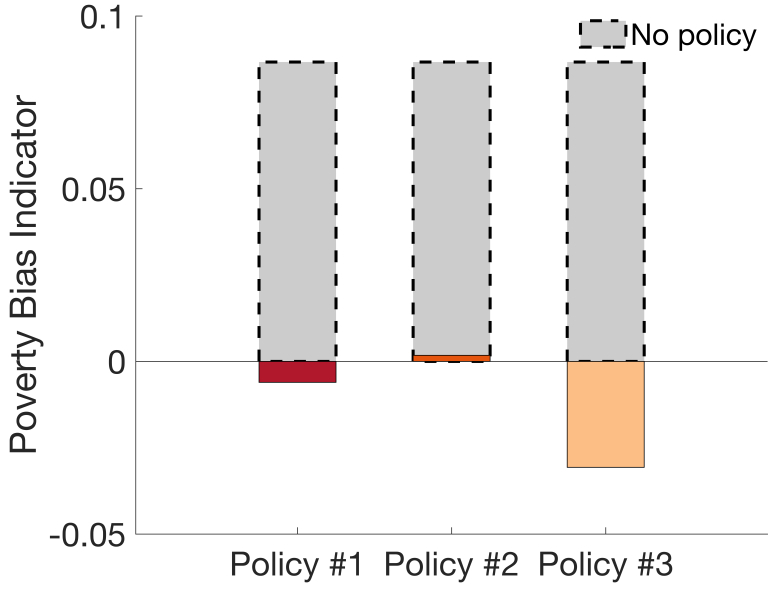

Figure 5.3: PBI_j under policies #1 to #3 (and no policy) averaged across the 500 sets of generated GMFs.

Chapter 6

Conclusions and future work

We present a new approach for assessing the effectiveness of DRR policies in mitigating positive post-earthquake relocation decision-making. The approach involves enriching an existing framework that integrates social and physical considerations for risk-informed policy design (Wang et al., 2023) with local perspectives and an accompanying data-driven model for estimating context-specific post-earthquake household relocation decision-making.

We develop a random forest data-driven model using local perspectives in the form of Nepali household survey data collected in the wake of the 2015 $M7.8$ and $M7.3$ Gorkha earthquakes, to assess post-earthquake relocation inclinations of local households. This model accounts for various household-level factors related to post-earthquake household relocation decision-making, i.e., residential damage, livelihood impact, place satisfaction, access to government funding, age of the household head, household income group, gender of the household head, and household size. In light of the general lack of (data-driven) models focusing on household relocation inclination (or decision-making), the model developed here serves as a novel risk-sensitive planning tool that provokes discussion on a complex multi-disciplinary social phenomenon.

We demonstrate the enhanced framework and the data-driven model developed by assessing the effects of multiple DRR policies for an expanding virtual urban testbed Tomorrowville, which is largely informed by data from the Kathmandu Valley, Nepal. We particularly focus on the extent to which the policies mitigate positive post-earthquake relocation inclination among low-income households. The case study reveals that a soft policy of post-disaster livelihood assistance provision for all households impacted by earthquake-induced unemployment (policy #1) is more effective in mitigating positive post-earthquake relocation inclination than hard policies centred on the seismic strengthening of physical infrastructure (policies #2 and #3). This emphasises the fact that hard strategies, consisting of resource-intensive engineering interventions, might not always be the most effective seismic risk reduction solution for urban areas exposed to seismic hazard. We also find that policy #1 is pro-poor overall (i.e., has a negative mean PBI_j value), despite providing assistance to households of all income groups. While this finding is limited to the case study's specific context, it suggests that opportunities exist for designing pro-poor DRR policies without the need to explicitly account for income thresholds, which can be politically sensitive (Lyon and Sepulveda, 2009).

Our framework is explicitly forward-looking, i.e., it quantifies earthquake risks of urban communities accounting for uncertain future development in yet-to-be urbanised regions. Many of these regions (e.g., the Kathmandu Valley, Nepal) are experiencing rapid expansion and population growth, which could significantly intensify natural-hazard exposure and vulnerability in the absence of risk-sensitive planning tools and policies like those proposed here (Mesta et al., 2022, 2023). A forward-looking perspective is particularly important for designing DRR policies related to post-earthquake household relocation decision-making; our framework can help to prevent relocation-related accumulation of vulnerabilities from the outset and address the root causes of exacerbating inequalities in the wake of a future earthquake disaster.

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