doi:10.26443/seismica.v3i2.1374

SEISMICA

Population displacement after earthquakes: benchmarking predictions based on housing damage

Nicole Paul * [1], **Carmine Galasso** [2], **Vitor Silva** [3,4], **Jack Baker** [5]

[1]PhD Candidate, University College London, London, UK, [2]Professor, University College London, London, UK, [3]Head of Risk Engineering, Global Earthquake Model Foundation, Pavia, Italy, [4]Researcher, University of Aveiro, Aveiro, Portugal, [5]Professor, Stanford University, Stanford, USA

Author contributions: *Conceptualization*: All authors. *Software*: Nicole Paul, Vitor Silva. *Validation*: Carmine Galasso, Vitor Silva, Jack Baker. *Formal Analysis*: Nicole Paul. *Writing - Original draft*: Nicole Paul. *Writing - Review & Editing*: All authors. *Visualization*: Nicole Paul. *Supervision*: Carmine Galasso, Vitor Silva, Jack Baker. *Funding acquisition*: Carmine Galasso, Nicole Paul.

Abstract In the aftermath of an earthquake, the number of residents whose housing was destroyed is often used to approximate the number of people displaced (i.e., rendered homeless) after the event. While this metric can provide rapid situational awareness regarding potential long-term housing needs, more recent research highlights the importance of additional factors beyond housing damage within the scope of household displacement and return (e.g., utility disruption, tenure, place attachment). This study benchmarks population displacement estimates using this simplified conventional approach (i.e., only considering housing destruction) through three scenario models for recent earthquakes in Haiti, Japan, and Nepal. These model predictions are compared with officially reported values and alternate mobile location data-based estimates from the literature. The results highlight the promise of scenario models to realistically estimate population displacement and potential long-term housing needs after earthquakes, but also highlight a large range of uncertainty in the predicted values. Furthermore, purely basing displacement estimates on housing damage offers no view on how the displaced population counts vary with time as compared to more comprehensive models that include other factors influencing population return or alternative approaches, such as using mobile location data.

Production Editor:
Gareth Funning
Handling Editor:
Pablo Heresi
Copy & Layout Editor:
Hannah F. Mark

Received:
May 6, 2024
Accepted:
October 11, 2024
Published:
October 28, 2024

1 Introduction

An average of 24 million annual displacements were triggered by disasters between 2008 and 2018, approximately three times greater than those triggered by conflict and violence (IDMC, 2019). The number of people displaced annually is likely to increase under ongoing trends, driven by poorly managed urban growth in hazard-prone areas, and potentially exacerbated by climate change effects. Despite this scale of human impact, disaster risk models have primarily focused on quantifying economic losses due to direct physical damage.

In earthquakes, the conventional practice for calculating the population displaced assumes that direct physical damage can render housing uninhabitable, thereby dislocating residents (see Fig. 1). Although housing damage has often been considered a primary driver of both initial displacement and potential long-term housing needs, more recent studies have highlighted the importance of additional factors beyond housing damage that influence displacement duration and population return. These additional factors span across the categories of physical damage to the built environment (e.g., utility disruption, reconstruction time), psychological and social phenomena (e.g., place attachment, social capital), household demographics (e.g., tenure, socioeconomic status), and pre- and post-disaster policies (e.g., permanent or temporary housing reconstruction programs, rental subsidies; Paul et al., 2024). Recent studies of population displacement after earthquakes have begun to incorporate these additional factors and explicitly capture population return (e.g., Burton et al., 2019; Bhattacharya and Kato, 2021; Grinberger and Felsenstein, 2016; Costa et al., 2022). Although these modeling improvements are promising, validation of the conventional approach (i.e., estimating population displacement based on housing destruction alone) has yet to be performed.

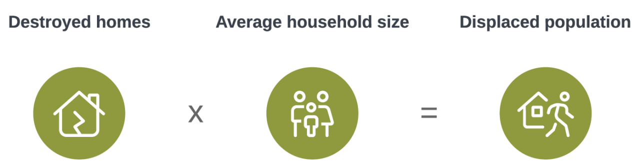

Figure 1 An illustration of the conventional practice for estimating population displacement after disaster events.

This study aims to benchmark the conventional practice within earthquake risk models of using housing destruction as the sole driver of population displacement. We compare these model-based estimates with officially reported statistics and alternative estimates

*Corresponding author: nicole.paul.22@ucl.ac.uk

derived from mobile location data, allowing us to understand this conventional approach's prediction potential and uncertainty range. Additionally, this study provides an initial attempt to validate risk model outputs (i.e., housing damage and population displacement estimates), a broader challenge within disaster risk assessment (e.g., Beguería, 2006; Ward et al., 2020; Crowley et al., 2020). Despite the importance of population return and the duration of displacement, this benchmarking study is limited to single snapshot values of displaced population counts that represent potential long-term housing needs.

2 Quantifying disaster displacement

2.1 Population displacement metrics

Researchers have highlighted a lack of consistent terminology regarding population displacement in disasters (e.g., Esnard and Sapat, 2014; Greer, 2015; Paul et al., 2024). This inconsistent use of terminology complicates efforts to quantify and interpret displacement metrics. The Internal Displacement Monitoring Centre (IDMC) defines displacement as "involuntary or forced movements [⋯] of individuals or groups of people from their habitual places of residence" that can be triggered by disasters or other causes such as conflict and violence or development projects (IDMC, 2020). As a part of their Global Internal Displacement Database (GIDD) initiative, the IDMC gathers information on various metrics associated with displacement after disaster events (IDMC), including:

- **Evacuations:** People leaving their habitual residence in advance of or during the onset of a hazard. These estimates are based on the population covered by mandatory or advisory evacuation orders, which are triangulated with evacuation centre headcounts (IDMC, 2018). Evacuations are typically assumed to be relatively short-term, however, there is ample evidence that not all households that evacuate are able to return in a timely manner (McAdam, 2022).
- **Sheltered populations:** People accommodated in shelters or relief camps provided by national authorities or other organizations. These estimates are more typically available using headcounts from the relevant authorities or organizations.
- **Population rendered homeless:** People that are displaced due to disaster-induced housing destruction. The IDMC typically estimates this value by multiplying the reported housing destruction counts from government agencies, UN organizations, or local authorities by the average household size. This metric is most similar to past attempts to quantify displacement within the earthquake engineering discipline (also known as "dislocation" ; Lin, 2009). In contrast to evacuations, this metric is more representative of potential long-term housing needs (Guadagno and Yonetani, 2023). This is the conventional approach within disaster risk models noted herein.

In general, each of these metrics of population displacement is reported as single snapshot values rather than as a time series. While each of these metrics are recorded by IDMC to inform their internal triangulation and quality assurance processes, the specific metric reported and underlying data source are not made publicly available in the GIDD.

2.2 Proxies for estimating displacement

It is difficult to get reliable estimates of population movements following disaster events. Households that evacuate or dislocate may stay with family and friends, stay in hotels or rentals, remain outdoors (e.g., in tents or their car), or seek public shelter. While headcounts of sheltered populations can be relatively straightforward, often only a small subset of the displaced population seeks public shelter (Quarantelli, 1982, 1995; IDMC, 2022a,b), and data regarding those that seek accommodation elsewhere is difficult to ascertain. As such, a variety of approaches have been used to estimate population displacement following disasters. Some of the common proxies used to estimate population displacement after disaster events are shown in Fig. 2. Further information about each proxy is provided in this section.

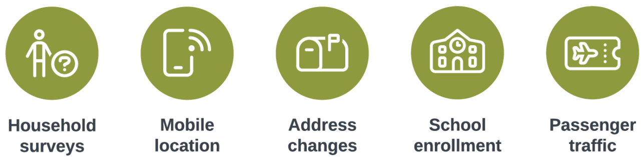

Figure 2 Common proxies for measuring population displacement after disaster events.

Household surveys and interviews have long been employed to understand disaster impacts on individual households. These can broadly be categorized as cross-sectional or longitudinal studies. Cross-sectional studies gather observations at a single point in time, providing a snapshot at that moment. In some cases, there are multiple observation windows, but each uses a different sample population. Longitudinal studies draw repeated observations over time from the same sample of households, tracking changes over time amongst that sample population. The vast majority of household displacement surveys in the disaster literature take a cross-sectional approach (e.g., Kolbe et al., 2010; Mayer et al., 2020; Cong et al., 2018; Lee et al., 2017; Elliott and Pais, 2006; Groen and Polivka, 2010). These studies provide rich information about that snapshot in time (e.g., one month after the disaster, two years after the disaster) and for that specific disaster and sample population. However, extending findings to other time windows for the same event is difficult. Another concern with this approach is the sample's representativeness, as displaced households are hard to identify (e.g., they are inaccessible in door-to-door visits, and mail may not be forwarded to their current address). Specific sampling methods have been employed to mitigate this challenge, such as surveying at local community events or at community shelters (e.g., Binder et al., 2015; Nejat and Ghosh, 2016) and through snowball sampling (i.e., asking participants to refer other participants who meet the study criteria; see Nejat and Ghosh, 2016, for an example of this approach). Some recent studies have taken a longitudinal approach (e.g., The Asia Foundation, 2019; Lines et al., 2022; Van De Lindt et al., 2020), which provides a richer context for those communities and disaster events. However, longitudinal surveys suffer attrition challenges (i.e., the loss of participants over time, which can affect the sample's representativeness) and costliness, making it difficult to scale across several communities and disaster events for a broader understanding of disaster recovery.

In recent years, mobile location data has been explored as a proxy for population displacement and return. In one of the first studies, Lu et al. (2012) used call detail records to estimate that the population of Port-au-Prince, Haiti, decreased by a maximum of 23% after the 2010 Haiti earthquake and that the destinations of households were highly correlated with the locations where they had social bonds (i.e., where they spent their time during holidays such as Christmas and New Year's). Mobile location data seems promising, as it can continuously capture how populations move across both time and space, potentially informing post-disaster planning needs in real-time and enabling data-driven retrospective studies. The validity of this proxy relies on the movements of those with mobile phones being similar to the movements of the overall disaster-affected population. Concerns regarding sample representativeness may be higher in countries where mobile phone ownership is limited or potentially correlated with factors such as housing quality, homeownership, or income level. Yabe et al. (2022) reviewed the potential use of mobile location data for capturing disaster impacts, classifying three main sources: call detail records, smartphone GPS data from location intelligence firms, and smartphone GPS data from major tech firms.

- **Call detail records (CDRs):** In contrast to the other two categories, this category is not reliant on smartphone ownership but on broader mobile phone ownership, covering a more substantial subset of the population. These records include the location of nearby cellphone towers when users call or send text messages. As a result, there is a lower spatial and temporal resolution than with the GPS datasets from smartphones. Some example studies using CDRs to track population displacement after disasters include Bengtsson et al. (2011), Lu et al. (2012), and Wilson et al. (2016).

- **Smartphone GPS data from location intelligence firms:** Several location intelligence firms, which collect and aggregate data from various third-party smartphone applications, have emerged in recent years. Precise location information could theoretically be available, but some form of spatial aggregation is typically required to alleviate data security/privacy concerns. Additionally, data may not be available over the full disaster recovery timeline, as many location intelligence firms shuffle unique device identifiers after a set period of time (e.g., every few months, every year) to preserve data contributors' privacy. There is often limited transparency in the data generation process, and these firms cover fewer countries. Some example studies using smartphone GPS data from location intelligence firms include Yabe et al. (2021, 2020) and Lee et al. (2022).

- **Smartphone GPS data from major tech firms:** Major tech firms can collect GPS location data from their users directly rather than rely on third-party services. Under specific agreements, these firms may provide processed forms of this data, aggregated in both time and space to address data security/privacy concerns. However, this data is often only tracked for more limited periods and may not cover the entire recovery timeline (e.g., Meta Data for Good records data for up to three months after a disaster event). These outputs are generally restricted to select products produced by each tech firm, with a limited ability to modify those selected metrics. An example study using smartphone GPS data from a major tech firm includes Yabe et al. (2019).

Data on mailing address changes of households in disaster-affected communities has been explored as a proxy for understanding disaster migration, such as from postal redirection records, voter registration data, or consumer credit reports (e.g., Plyer et al., 2010; DeWaard et al., 2019, 2020; Hinojosa, 2018; Price, 2011). Postal redirection data can be a useful way to understand the destination communities of displaced households (e.g., what proportion of households redirect to their origin community versus an alternate community). However, it seems unlikely that households that are displaced for short periods (e.g., evacuate for less than a week) would either voluntarily submit a change of address (Plyer et al., 2010) or be automatically detected by algorithms used to determine an individual's most-likely mailing address (such as those used by consumer credit reports). For example, DeWaard et al. (2019) found the proportion of displaced households that returned within 12 months of Hurricanes Katrina, Harvey, and Maria in the United States ranged from 12% to 38% using data from the Consumer Credit Panel. This would imply that over half of the households did not return within a year of each event, indicating a sample that was heavily affected or that otherwise anticipated more permanent moves. The quarterly sampling frequency likely influences these results, as displacement durations of less than three months seem unlikely to be counted in this approach.

Some studies have explored using school enrollment data to understand migration and return after disasters (e.g., Sharygin, 2021; Hinojosa and Meléndez, 2018; Newell et al., 2012). An implicit assumption in the representativeness of this proxy is that the movement of households with children enrolled in public schools resembles that of the broader affected population. The viability of these datasets in tracking longitudinal displacement will vary depending on the sampling frequency of the relevant administrative area. For example, many different states within the United States theoretically capture continuous data on student transfers, but in practice, the accuracy is limited beyond the official school census dates (e.g., early October for California). In contrast, monthly estimates were available to track student movement in New Zealand after the Christchurch earthquake on February 22, 2011 (Newell et al., 2012).

Passenger traffic data can have higher sampling frequencies. For example, daily arrival and departure cards for those on international flights before and after the 2010-11 Canterbury earthquake sequence in New Zealand (Newell et al., 2012) or monthly net movement of air travel passengers data before and after Hurricane Maria in Puerto Rico (Hinojosa and Meléndez, 2018). However, these datasets have limited relevance beyond movements out of island communities or across international boundaries, as a consistent observation after past events is that displaced households usually move short distances (e.g., Nawrotzki et al., 2014; Sharygin, 2021; Love, 2011).

Since mobile location data appears to be an emerging and promising source of population displacement estimates, this study includes benchmarks from available literature using such approaches (FlowMinder, 2021; Yabe et al., 2020; Wilson et al., 2016). However, it is acknowledged that no standard approach was undertaken in these studies. Differences among the considered mobile location data studies include the primary data source used (i.e., CDRs versus smartphone GPS data), the data provider and their associated sampling rate, the displacement criteria established, and the analysis methodology employed.

3 Past earthquake scenario models

3.1 Overview of the scenario models

In this section, the term "scenario model" is used rather than the more general term "disaster risk model" to distinguish the fact that a single earthquake rupture is modeled rather than a set of rupture events (Silva, 2016, 2018). This study benchmarks a conventional scenario model-based approach against other available estimates for recent earthquake events. These estimates include reported impacts from official statistics or the IDMC and mobile location data-based estimates published in the literature. While the scenario model-based estimates in this study typically follow the same underlying assumption as the reported figures from official statistics or the IDMC (i.e., housing destruction displaces residents), the ground shaking is simulated based on the earthquake rupture characteristics, resulting ground shaking local intensity estimates, and any available seismic station data in the study area rather than assumed from official reports. Additionally, the distribution of occupants is more refined (i.e., different building types have different numbers of occupants rather than using a single average household size) and the damage assessment is performed using analytical fragility models (i.e., based on simulated damage rather than using observed empirical damage). As such, the results from the benchmarking study allow us to evaluate the prediction potential and uncertainty range of earthquake scenario models. Such models might be used to assess disaster risk potential in terms of population displacement for future events and evaluate the cost-benefit of potential mitigation strategies (alongside other risk metrics or decision variables; e.g. Liel and Deierlein, 2013; Cremen et al., 2022; Hoyos and Silva, 2022).

3.2 Selection of past earthquake events

Three recent earthquakes were selected, as summarized in Tab. 1. These events were selected based on the following criteria:

- **Recency:** The exposure model used herein (described in the next section; Yepes-Estrada et al., 2023) is representative of the year 2021. Therefore, the modeled populations may not represent past decades, particularly if there has been significant population growth or decline in recent years.
- **Availability of mobile location data studies:** Many approaches to estimating population displacement assume housing destruction as the primary driver; thus, studies using mobile location data were targeted to include an estimate that is not reliant on the same assumption.
- **Geographic coverage:** The events were selected to cover a range of geographic locations, which entail different tectonic regions, standard construction practices (and associated physical vulnerability of the building stock), and levels of data availability.

Country	Name/Location	M_W	Date
Haiti	Nippes	7.2	August 14, 2021
Japan	Kumamoto	7.0	April 16, 2016
Nepal	Gorkha	7.8	April 25, 2015

Table 1 Selected earthquake scenarios for the benchmarking study.

3.3 Data collection and input models

Two primary data sources were used to derive the scenario models discussed herein, both courtesy of the Global Earthquake Model (GEM) Foundation. These data sources are described further in this section.

The GEM Earthquake Scenario Database (GEM ESD) is an ongoing initiative within the GEM Foundation to collect information about past earthquake events, including ground shaking from seismic stations and macroseismic intensity estimates, rupture model definitions (i.e., magnitude, geometry, mechanism), candidate ground motion models (GMMs), and impact data (e.g., reported deaths, injuries, damages). This repository is publicly available at: https://github.com/gem/earthquake-scenarios. For this study, ground shaking

Earthquake	Seismic stations	Rupture model	Selected GMM
M_W7.2 Nippes	USGS[1] (us6000f65h)	USGS finite fault model (us6000f65h)	Akkar et al. (2014)
M_W7.0 Kumamoto	USGS[1] (us20005iis) NIED[2]	USGS fault rupture model (us20005iis)	Chiou and Youngs (2014)
M_W7.8 Gorkha	USGS[1] (us20002926) CESMD[3] Bhattarai et al. (2015)	Hayes et al. (2015)	Atkinson and Boore (2003)

[1]US Geological Survey (USGS) ShakeMap's station list (https://earthquake.usgs.gov/data/shakemap/)
[2]National Research Institute for Earth Science and Disaster Prevention (NIED)'s strong motion seismograph networks (https://www.kyoshin.bosai.go.jp/)
[3]Center for Engineering Strong Motion Data (CESDMD)'s archive (https://www.strongmotioncenter.org/)

Table 2 Summary of key inputs to the scenario hazard model component.

estimates from seismic stations, rupture model definitions, and candidate GMMs were taken from this repository to develop the hazard model component. Tab. 2 presents a summary of the primary sources of data used. Although multiple rupture models and candidate GMMs are available in the GEM ESD, a single combination was chosen for each earthquake scenario based on the consistency of the simulated median ground motion fields with the observations from seismic stations. Additionally, the soil conditions (i.e., shear wave velocity in the upper 30 meters; $V_{S,30}$) at each site were derived using the global hybrid $V_{S,30}$ map from the United States Geological Survey (Heath et al., 2020).

This benchmarking study also uses model components from version 2023.0.0 of GEM' s Global Risk Model (Silva et al., 2020). In particular, the residential exposure models for Haiti, Japan, and Nepal from the Global Exposure Model (Yepes-Estrada et al., 2023) and the structural fragility functions from the Global Vulnerability Model (Martins and Silva, 2021). The exposure models include building counts, the number of occupants, and building typologies, which are based primarily on national statistics, further adjusted to represent the year 2021 (i.e., to account for population growth or decline in each administrative area). The structural fragility models are defined for each building class within the exposure model for four discrete damage states: slight, moderate, extensive, and complete damage. These four damage states roughly correspond to the five damage states in the European macroseismic scale (EMS-98; Grünthal, 1998), except that the complete damage state in OQ encompasses both the fourth damage state and the fifth damage state in EMS-98 (i.e., heavy structural damage with very heavy nonstructural damage and very heavy structural damage). Further documentation on the fragility derivation process can be found at: https://docs.openquake.org/vulnerability/.

For this benchmarking study, it is assumed that all occupants within extensively and completely damaged buildings would be rendered homeless. That is, dwellings in the extensive damage state (i.e., moderate structural damage and heavy nonstructural damage) or complete damage state (i.e., heavy structural damage or beyond) are assumed to be "uninhabitable," thereby displacing their occupants. Although this assumption is held constant for each of the three earthquake scenarios, it is possible that different countries or communities would exhibit different behaviors or relationships between housing damage and dislocation. For example, some areas could require building inspection prior to re-occupancy even at more moderate levels of damage or mandate evacuations in light of potential aftershocks. Further, different dwelling types could have stricter requirements for re-occupancy, such as requiring water and power availability for fire-safety in multistorey apartment buildings. However, the assumption taken herein seems most consistent with IDMC, one of the key benchmarks included in this study.

3.4 Scenario analysis methodology

The scenario analyses are performed using the OpenQuake Engine (OQ), an open-source seismic hazard and risk analysis software (Silva et al., 2014). To leverage observed data from recording stations, the scenario calculator within OQ has been extended to condition ground motion fields using data from seismic stations following the procedure proposed in Appendix B by Engler et al. (2022). Uncertainties in the hazard component (i.e., source model and GMMs) have previously been identified to dominate the uncertainty in regional risk predictions (Kalakonas et al., 2020) and there is evidence that incorporating observational data from recording stations improves the accuracy and precision of scenario loss estimates (Silva and Horspool, 2019).

For this study, 1,000 Monte Carlo samples of cross-spatially correlated ground motions conditioned on available seismic station data are generated for each event. The median estimates across all 1,000 realizations for each scenario are visualized in Fig. 3.

For each simulated ground motion field, a damage state is sampled for each asset in the exposure model using the associated fragility curves for that asset (based on the building typology) and the corresponding ground motion intensity measure (from the simulated ground motion field). The damage state for each asset in each realization is then directly mapped to the displacement consequence (i.e., 100% displaced in the complete and extensive damage state, 0% otherwise) and multiplied by the number of occupants in that asset.

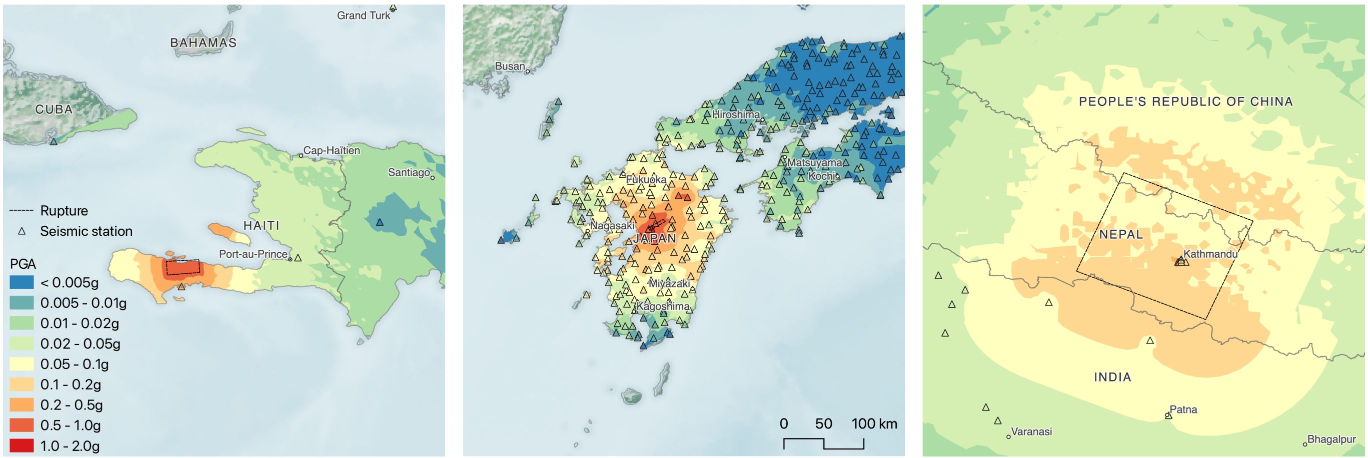

Figure 3 Median peak ground acceleration (PGA) for each scenario earthquake, from left to right: 2021 M_W7.2 Nippes in Haiti, 2016 M_W7.0 Kumamoto in Japan, and 2015 M_W7.8 Gorkha in Nepal. Available recording station PGA values are shown as triangles, which were used to condition the simulated ground motion fields.

Country	Source	Damaged housing	Destroyed housing
All	This study (OQ)	Slight	Extensive
		Moderate	Complete
Haiti	CDEMA (2021)	Damaged	Destroyed
Japan	JCO (2017)	Partially damaged (一部破損)	Partially destroyed (半壊)
			Completely destroyed (全壊)
Nepal	ICIMOD (2015)	Partially damaged	Fully damaged

Table 3 Mapping of reported damage states to aggregate housing damage and destruction.

4 Benchmarking study results

4.1 Selected metrics for comparison

The metrics for this benchmarking study include housing damage and destruction counts, as well as any available displacement figures (i.e., sheltered population, population rendered homeless, and the number of evacuations).

As discussed above, four damage states are included in the OQ scenario models (i.e., slight, moderate, extensive, and complete). However, different entities may define damage states differently. For example, the Japanese Cabinet Office (JCO) identifies the following building damage states: partially damaged (一部破損), partially destroyed (半壊), and completely destroyed (全壊; JCO, 2017). To facilitate comparison, the different reported damage states are summed into the categories "damaged" and "destroyed," where destroyed dwellings are considered uninhabitable and damaged dwellings suffered some damage (but are not destroyed). The assumed mapping is shown in Tab. 3.

Similarly, different sources report displacement figures using a different basis for the metric (i.e., rendered homeless, sheltered, evacuated). Unlike damage, it is unrealistic to sum the various metrics to get an aggregate value, as there may be considerable overlap between individuals who evacuate, are rendered homeless, or are accommodated in shelters. Thus, the maximum estimate is used if a source reports multiple metrics.

The criteria used to estimate displacement using mobile location data can also vary and is summarized below for the referenced studies:

- **Haiti's 2021 M_W7.2 Nippes earthquake:** Based on CDRs where mobile users "moved from their pre-earthquake usual locations" within the Grand'Anse, Sud, and Nippes departments during the first week after the earthquake (FlowMinder, 2021).
- **Japan's 2016 M_W7.0 Kumamoto earthquake:** "The rate of affected users who stayed outside their home [shichoson (cities/wards)] out of all affected users" on the day of the earthquake using smartphone GPS data (Yabe et al., 2020).
- **Nepal's 2015 M_W7.8 Gorkha earthquake:** The "people above normal levels [that] had left the [Kathmandu] valley"" in the first three weeks after the earthquake, per CDRs (Wilson et al., 2016). This refers to the number of post-earthquake outflows in excess of the pre-earthquake outflows during the benchmark period (January 1, 2015 through April 7, 2015).

4.2 Haiti's 2021 M_W7.2 Nippes earthquake

A comparison of the results for the 2021 Nippes earthquake is shown in Tab. 4 and Fig. 4. For this event, the IDMC based the displaced estimate on the reported housing destruction count from CDEMA (2021) and multiplied that by an average household size of 4.08.

In this case, the scenario model predicted similar average damage estimates (and therefore similar average displacement estimates) to official reports and the

	Scenario model	Reported		Mobile data
	This study (OQ)	CDEMA (2021)	IDMC	FlowMinder (2021)
Damaged houses	**115,747**	**83,770**	**n. r.**	**n. r.**
Slight	88,692	n. r.	n. r.	n. r.
Moderate	27,056	n. r.	n. r.	n. r.
Destroyed houses	**48,913**	**53,815**	**n. r.**	**n. r.**
Extensive	13,302	n. r.	n. r.	n. r.
Complete	35,611	n. r.	n. r.	n. r.
Displaced	**209,059**	**n. r.**	**220,000**	**90,000**
Sheltered	n. r.	n. r.	n. r.	n. r.
Evacuated	n. r.	n. r.	n. r.	90,000
Homeless	209,059	n. r.	220,000	n. r.

Table 4 Comparison of results for the 2021 M_W7.2 Nippes earthquake in Haiti; "n. r." indicates the value was not reported in that source.

IDMC. In contrast, the mobile location data-based estimate predicted approximately half the number of displacements.

Notably, the criteria used for the mobile location data-based estimate was described as "moved from their pre-earthquake usual locations" in the first week after the earthquake. However, the spatial resolution used in their assessment was unspecified; therefore, it is possible that a significant population remained near their usual location but remained outside their habitual residence (e.g., stayed outside or in a tent due to fear of aftershocks and/or to protect their property). This highlights a potential challenge of using mobile location data as a proxy for population displacement in disasters: physical return to a 'home' location does not necessarily signify that a durable solution (e.g., stable housing) has been found.

Additionally, the mobile location data-based estimates assume that the movement of the sample population (i.e., those with SIM cards) is representative of the overall population, which may not be the case if phone ownership and/or the damage experienced is not uniform across population subgroups. There were approximately 64 mobile cellular subscriptions per 100 people in Haiti in the year of this earthquake, which is notably lower than the global average of 108 (World Bank Group, 2021). Past studies investigating the use of mobile location data in low- to middle-income countries have found that mobile phone owners tend to be wealthier and more highly educated (Blumenstock and Eagle, 2010; Wesolowski et al., 2012; Frias-Martinez and Virseda, 2012), and that higher income groups tend to travel further and more frequently in baseline conditions (e.g., Wesolowski et al., 2012). On one hand, baseline mobility estimates (i.e., irrespective of disasters) using CDRs have been found to be surprisingly robust despite these differences in mobile phone ownership (Wesolowski et al., 2013), especially as compared with smartphone-based estimates (Milusheva et al., 2021). On the other hand, these studies do not consider sudden-onset hazards and the potential role of damage in forcing movement away from habitual dwelling units (i.e., disaster displacement). There is also evidence that households with lower socioeconomic status tend to experience more damage in disasters (e.g., Hallegatte et al., 2020). If those with mobile phones are less likely to experience significant damage than those without mobile phones, estimates using this approach are likely to be biased.

Lastly, although all estimates are within the modeled distribution, the range of values is significant (112k to 306k displaced for ± one standard deviation).

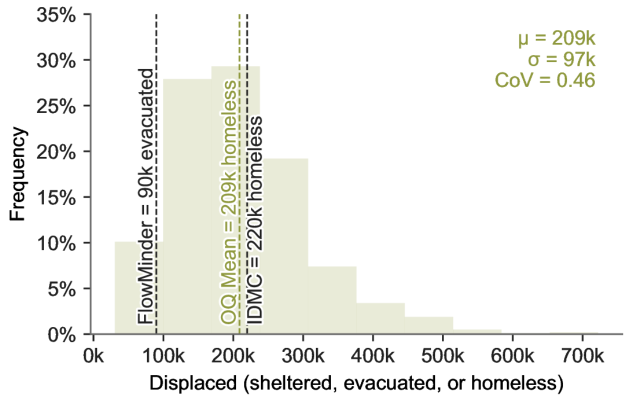

Figure 4 The modeled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2021 M_W7.2 Nippes earthquake in Haiti.

4.3 Japan's 2016 M_W7.0 Kumamoto earthquake

The comparison of results for the 2016 Kumamoto earthquake is shown in Tab. 5 and Fig. 5. In this case, the IDMC directly adopted the sheltered estimates from the Japanese Cabinet Office.

For this event, the scenario model again predicted average damage and displacement estimates similar to those of the reported data. Despite the similarity between the average scenario model estimates and the reported values, there is a notable discrepancy between the average buildings estimated in complete damage in OQ and reported as completely destroyed (全壊) by the official statistics, which could be in part due to varying damage state definitions. The Japan Cabinet Office reports standard statistics after earthquake events, including the number sheltered and the number under evacuation orders. Interestingly, the number sheltered in this earthquake greatly exceeds those under evacuation orders or advisories. This contradicts findings from disasters in the United States and the Pacific Islands, whereby

	Scenario model	Reported		Mobile data Yabe et al. (2020)*	
	This study (OQ)	JCO (2017)	IDMC	Day 0	Day 160
Damaged houses	**150,072**	**155,902**	**n. r.**	**n. r.**	**n. r.**
Slight	104,502	n. r.	n. r.	n. r.	n. r.
Moderate	45,570	n. r.	n. r.	n. r.	n. r.
Destroyed houses	**65,066**	**42,716**	**n. r.**	**n. r.**	**n. r.**
Extensive	23,911	34,037	n. r.	n. r.	n. r.
Complete	41,155	8,679	n. r.	n. r.	n. r.
Displaced	**218,708**	**196,325**	**196,300**	**308,422**	**154,816**
Sheltered	n. r.	196,325	196,300	n. r.	n. r.
Evacuated	n. r.	1,224	n. r.	308,422	154,816
Homeless	218,708	n. r.	n. r.	n. r.	n. r.

**The displacement estimates in Yabe et al. (2020) are reported as rates (25.5% on the day of the mainshock and 12.8% 160 days after the mainshock); to convert the rate into an absolute value, the rate is multiplied by the estimated population in the 33 affected districts considered within that study.*

Table 5 Comparison of results for the 2016 M_W7.0 Kumamoto earthquake in Japan; "n. r." indicates the value was not reported in that source.

Prefecture	**Damaged houses**		**Destroyed houses**		**Displaced persons**	
	This study	Reported (JCO)	This study	Reported (JCO)	This study*	Reported (JCO)**
Kumamoto	112,959	147,563	60,730	42,497	204,721	183,882
Oita	9,076	8,062	2,331	231	6,520	12,443
Fukuoka	17,335	251	1,281	4	5,076	n. r.
Miyazaki	4,086	21	335	2	973	n. r.
Yamaguchi	710	3	16	n. r.	64	n. r.
Saga	3,317	1	266	n. r.	982	n. r.
Nagasaki	2,046	1	97	n. r.	334	n. r.
All other areas	543	n. r.	10	n. r.	38	n. r.

**The displaced persons estimates from the scenario models in this study (OQ) represent the population rendered homeless due to housing destruction*
***The displaced persons estimates from the reported source (JCO, 2017) is based on the max sheltered population counts*

Table 6 Comparison of subnational results for the 2016 M_W7.0 Kumamoto earthquake in Japan; "n. r." indicates the value was not reported in that source.

residents who evacuate seek public shelter only as a last resort (Quarantelli, 1982, 1995; IDMC, 2022a,b).

In this case, the initial mobile location data-based estimate exceeds the modeled and reported estimates but is of a similar magnitude. The estimated displacement rate over time is also provided by Yabe et al. (2020) as shown in Fig. 6, which shows reasonable consistency between the scenario model and the estimated displacement rate from mobile location data at 160 days after the earthquake. This supports the assumption that housing destruction-based displacement estimates might reasonably estimate long-term housing needs. However, the scenario model provides no view on the time period of the displaced estimate. Notably, there were 131 mobile cellular subscriptions per 100 people in Japan the year of this earthquake (World Bank Group, 2021). However, smartphone penetration during this time was lower (reported as 50.1%; Newzoo, 2017).

Since the JCO (2017) reports data at the subnational level, the damage and displacement estimates can be compared across prefectures as shown in Tab. 6. More variability across the estimated damage and displacement is evident at the prefecture-level, with the scenario model (OQ) notably overestimating impacts in Fukuoka relative to what was reported. This could be partially due to the conditioning of ground motion fields, where stations near to cities outlying the heavily-populated Fukuoka city recorded higher values of PGA than expected for the GMM employed. Since the ground motion fields are conditioned on the recording station data, the model correspondingly adjusts the inter-event term (bias) in the GMM for all sites and reduces the intra-event term at other sites inversely proportional to distance (using a cross-spatial correlation model). This can be observed in Fig. 3: while the estimated ground shaking mostly attenuates with distance from the rupture, there are some "islands" of relatively higher (or lower) ground shaking near to station observations. In the case of Fukuoka city, the station recorded relatively higher shaking, leading to higher damage counts than would have predicted without conditioning. While conditioning the ground motion fields on available observational data is appealing, there could also be situations where highly localized site conditions or station malfunction yield unrealistic predictions at the station site and neighboring sites (due to cross-spatial correlation). A higher density of stations, especially near heavily populated areas, could help mitigate this issue. More generally, the estimated damage and displacement is less concentrated in the scenario model as compared with what was reported. This may underscore the importance of incorporating on-the-ground observations to better-constrain engineering forecasts (Loos et al., 2020).

All population displacement estimates are well within the range of the modeled distribution. The range of values predicted by the model (130k to 308k displaced for ± one standard deviation) has a similar but slightly smaller range than in the 2021 Nippes earthquake in Haiti.

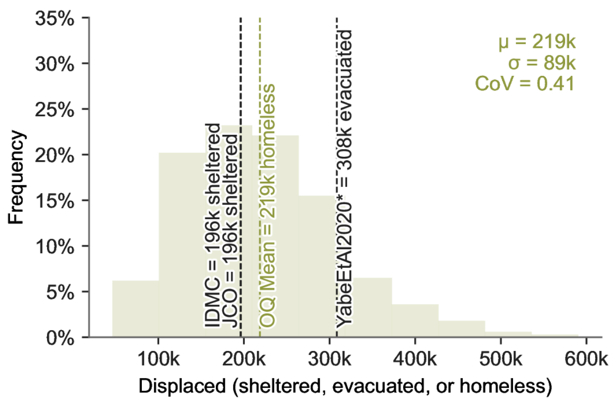

Figure 5 The modeled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2016 M_W7.0 Kumamoto earthquake in Japan.

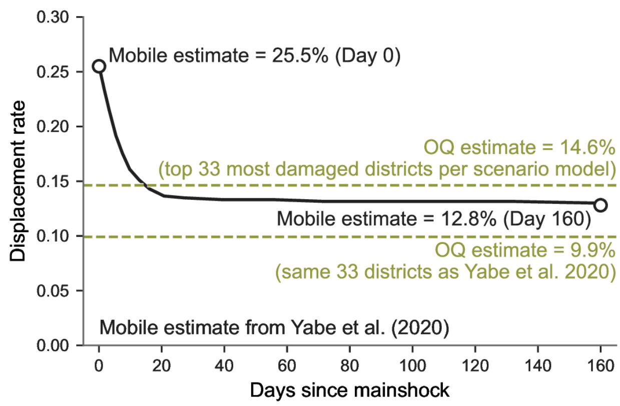

Figure 6 The estimated population displacement rate over time from mobile location data in Yabe et al. (2020) versus the estimated population displaced in this study (OQ) for the 2016 M_W7.0 Kumamoto earthquake in Japan.

4.4 Nepal's 2015 M_W7.8 Gorkha earthquake

The comparison of results for the 2015 Gorkha earthquake in Nepal is shown in Tab. 7 and Fig. 7. For this event, the IDMC estimated displacement based on the number of households identified as eligible for receiving the housing reconstruction grant per Nepal's Housing Recovery and Reconstruction Platform (HRRP), multiplied by an average household size of 4.3.

Although the average estimates of any level of damage (i.e., damaged plus destroyed) are similar between the model and the official statistics, the breakdown by severity (i.e., damaged versus destroyed) is notably different. These discrepancies could be exacerbated by the inapplicability of existing GMMs for this scenario: this was a continent-continent subduction zone earthquake, whereas existing subduction GMMs are primarily derived from data in ocean-continent or ocean-ocean subduction zones (Rajaure et al., 2017). However, past studies have indicated that Atkinson and Boore (2003) explains the available recorded PGA values well (Chadha et al., 2015; Hough et al., 2016). Beyond the hazard component, these discrepancies could also be driven by potential inaccuracies in the exposure model or associated fragility functions used for Nepal. Due to the discrepancy in damage estimates, the average displaced estimates are more markedly different than the other two earthquake scenarios.

The mobile location data-based estimate is significantly lower than the modeled and reported estimates, although this could be due to the criteria employed within that study ("people above normal levels [that] had left the [Kathmandu] valley" in the first few weeks after the earthquake). Under that criterion, individuals who may have left their habitual residence but remained in the Kathmandu Valley would not be counted, nor would individuals normally residing outside the Kathmandu Valley in the first place. According to data during the year of the earthquake, there were 100 mobile cellular subscriptions per 100 people in Nepal, much higher than in Haiti (World Bank Group, 2021).

Once again, all population estimates lie within the modeled distribution. However, the range of predicted values (1,012k to 2,592k displaced for ± one standard deviation) is significant and notably larger than the other two scenarios. This is likely due to a combination of the limited number of seismic stations (as compared with Japan) to properly condition the ground motion fields and the higher sigma within the selected GMM for this combination of magnitude and source-to-site distances.

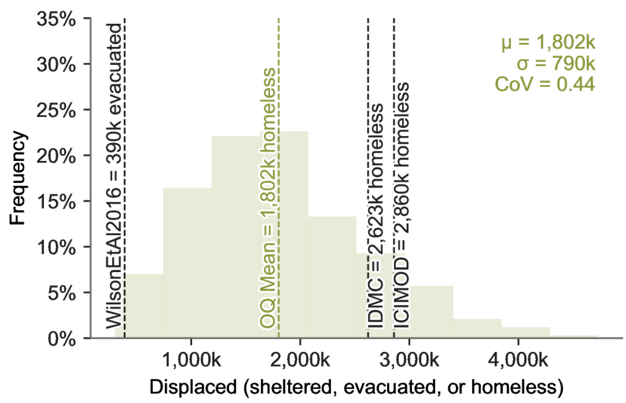

Figure 7 The modeled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2021 M7.8 Gorkha earthquake in Nepal.

5 Conclusions

This benchmarking study compares population displacement estimates for recent earthquake events in Haiti, Japan, and Nepal, which is summarized in Fig. 8.

	Scenario model	Reported		Mobile data
	This study (OQ)	ICIMOD (2015)	IDMC	Wilson et al. (2016)
Damaged houses	**810,176**	**282,300**	**n. r.**	**n. r.**
Slight	599,480	n. r.	n. r.	n. r.
Moderate	210,696	n. r.	n. r.	n. r.
Destroyed houses	**284,604**	**508,215**	**n. r.**	**n. r.**
Extensive	98,961	n. r.	n. r.	n. r.
Complete	185,643	n. r.	n. r.	n. r.
Displaced	**1,802,535**	**2,860,000**	**2,623,000**	**390,000**
Sheltered	n. r.	n. r.	n. r.	n. r.
Evacuated	n. r.	n. r.	n. r.	390,000
Homeless	1,802,535	2,860,000	2,623,000	n. r.

Table 7 Comparison of results for the 2015 M_W7.8 Gorkha earthquake in Nepal; "n. r." indicates the value was not reported in that source.

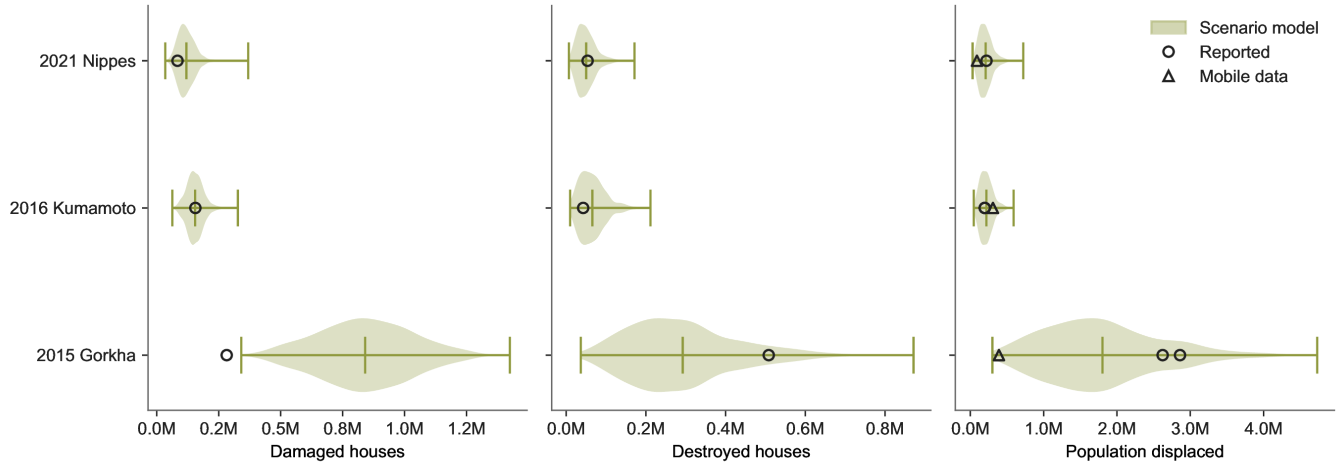

Figure 8 Summary of the key benchmarking results for housing damage, housing destruction and population displacement in the following earthquakes: 2021 M_W7.2 Nippes in Haiti, 2016 M_W7.0 Kumamoto in Japan, and 2015 M_W7.8 Gorkha in Nepal.

The conventional practice in earthquake risk assessment is to consider housing destruction as the sole driver of population displacement, which is implemented in the three scenario models herein. This conventional approach offers a way to estimate potential long-term housing needs, which can provide useful rapid situational awareness and inform early recovery decisions. The results of this simplified approach are compared with officially reported statistics and alternative mobile location data-based estimates.

The scenario model estimates are largely consistent with what was officially reported for these earthquake events, albeit with a large range of uncertainty. However, the official statistics are often underpinned by the same fundamental assumption (i.e., housing destruction leads to displacement). Thus, a fully independent comparison is not possible to validate the models. Additionally, scenario models require several assumptions across the rupture characterization, ground motion model selection, building and population exposure derivation, and fragility function assignment. Each of these model inputs influences the resulting risk estimates, and this epistemic uncertainty complicates comparisons. Various observational data could be used to better-constrain model predictions and reduce uncertainty: while this study only incorporated recorded ground shaking from seismic stations, other relevant sources of observational data, such as field surveys or remote sensing-derived damage data, could also potentially be incorporated (Loos et al., 2023). Validation is further complicated by the use of many different metrics to quantify displaced populations (i.e., rendered homeless, sheltered, evacuated). Moreover, neither the scenario models nor the official reports offered a view on population return or the duration of displacement.

Mobile location data could theoretically close the data gap on displacement duration and return, but those estimates are less consistent with the scenario model estimates and the officially reported data. In particular, the mobile location data-based estimates for the Nepal and Haiti earthquakes are much lower than the scenario model estimates and the officially reported estimates. These discrepancies could result from the criteria used to define displacement in these data-driven approaches or the un-representativeness of the data sample. In some cases, discrepancies may exist because the considered population is restricted to specific areas (e.g., within the Kathmandu Valley) or that there is an insufficient spatial resolution used in the displacement criteria (i.e., neglecting those who left their habitual residence but migrated short distances). In other cases, discrepancies could exist because the movements of the sample population (i.e., those with mobile phones) are not fully representative of the affected population (e.g., lower income populations may be less likely to have mobile phones and may experience disproportionate damage, elderly populations may be less likely to carry phones and may also inhabit older buildings more prone to damage). This data representativeness issue is likely even more prevalent in countries or communities with lower rates of mobile phone ownership. Further evaluation of both the displacement criteria and the sample population's representativeness may be required to instill confidence in the use of mobile location data to estimate population displacement after disasters.

The results from this benchmarking study demonstrate the potential use of disaster risk models to evaluate population displacement and potential long-term housing needs with minimal information. However, by only considering housing destruction, additional factors known to influence household displacement duration and return into the recovery phase (e.g., home ownership, place attachment, social capital) are neglected. Moreover, critical factors influencing shelter-seeking behavior (e.g., utility disruption, weather) are ignored. Thus, the standard practice of only considering housing destruction can provide useful, rapid situational awareness, but fails to capture a more holistic view of population displacement after disaster.

Ultimately, various metrics of population displacement (e.g., population rendered homeless due to housing destruction, evacuations in the emergency phase, shelter needs, return rates) can help expand the metrics quantified within "what-if" scenarios and inform cost-benefit studies to capture more equitable and people-centered metrics beyond economic loss.

Data and code availability

The GEM Foundation's Earthquake Scenario Database (ESD) is publicly available at https://github.com/gem/earthquake-scenarios.

The GEM Foundation's Global Exposure Model is publicly available at the first administrative level at https://github.com/gem/global_exposure_model. For finer resolutions, please send a request at https://www.globalquakemodel.org/products.

The software used to conduct the scenario analyses, OpenQuake, is open source and publicly available at https://github.com/gem/oq-engine. Training materials to learn how to use the OpenQuake Engine are freely available at https://www.training.openquake.org/.

Seismic station intensity estimates were downloaded from multiple sources, and combined into a consistent format for analysis.

- US Geological Survey (USGS) ShakeMap's station list (https://earthquake.usgs.gov/data/shakemap/)
- National Research Institute for Earth Science and Disaster Prevention (NIED)'s strong motion seismograph networks (https://www.kyoshin.bosai.go.jp/)
- Center for Engineering Strong Motion Data (CESDMD)'s archive (https://www.strongmotioncenter.org/)

Competing interests

The authors state that no competing interests influenced this study.

Acknowledgements

This work was partly funded by the University College London Overseas Research Scholarship (ORS) and the Willis Towers Watson Research Network.

Additionally, the authors thank the Global Earthquake Model (GEM) Foundation for providing access to the exposure and fragility models used in this study and the Internal Displacement Monitoring Centre (IDMC) for providing their triangulation data, which included further details on the displacement metric type and data source published within the Global Internal Displacement Database (GIDD).

References

Akkar, S., Sandıkkaya, M. A., and Bommer, J. J. Empirical ground-motion models for point-and extended-source crustal earthquake scenarios in Europe and the Middle East. *Bulletin of earthquake engineering*, 12:359–387, 2014.

Atkinson, G. M. and Boore, D. M. Empirical ground-motion relations for subduction-zone earthquakes and their application to Cascadia and other regions. *Bulletin of the Seismological Society of America*, 93(4):1703–1729, 2003.

Beguería, S. Validation and Evaluation of Predictive Models in Hazard Assessment and Risk Management. *Natural Hazards*, 37(3): 315–329, Mar. 2006. doi: 10.1007/s11069-005-5182-6.

Bengtsson, L., Lu, X., Thorson, A., Garfield, R., and Schreeb, J. v. Improved Response to Disasters and Outbreaks by Tracking Population Movements with Mobile Phone Network Data: A Post-Earthquake Geospatial Study in Haiti. *PLOS Medicine*, 8(8): e1001083, Aug. 2011. doi: 10.1371/journal.pmed.1001083.

Bhattacharya, Y. and Kato, T. Development of an Agent-Based Model on the Decision-Making of Dislocated People After Disasters. In Geertman, S. C. M., Pettit, C., Goodspeed, R., and Staffans, A., editors, *Urban Informatics and Future Cities*, The Urban Book Series, pages 387–406. Springer International Publishing, Cham, 2021. doi: 10.1007/978-3-030-76059-5_20.

Bhattarai, M., Adhikari, L. B., Gautam, U. P., Laurendeau, A., Labonne, C., Hoste-Colomer, R., Sèbe, O., and Hernandez, B. Overview of the large 25 April 2015 Gorkha, Nepal, earthquake from accelerometric perspectives. *Seismological Research Letters*, 86(6):1540–1548, 2015.

Binder, S. B., Baker, C. K., and Barile, J. P. Rebuild or Relocate? Resilience and Postdisaster Decision-Making After Hurricane Sandy. *American Journal of Community Psychology*, 56(1): 180–196, Sept. 2015. doi: 10.1007/s10464-015-9727-x.

Blumenstock, J. and Eagle, N. Mobile divides: gender, socioeconomic status, and mobile phone use in Rwanda. In *Proceedings of the 4th ACM/IEEE International Conference on Information and Communication Technologies and Development*, pages 1–10, London United Kingdom, Dec. 2010. ACM. doi: 10.1145/2369220.2369225.

Burton, H., Kang, H., Miles, S., Nejat, A., and Yi, Z. A framework and case study for integrating household decision-making into post-earthquake recovery models. *International Journal of Disaster Risk Reduction*, 37:101167, 2019.

CDEMA. Haiti Earthquake: Final Situation Report #12. Technical report, St. Michael, Barbados, Sept. 2021. https://www.cdema.org/images/2021/09/FINAL_CDEMA_Situation_Report_12_Haiti_Earthquake_14Sep2021.pdf.

Chadha, R. K., Srinagesh, D., Srinivas, D., Suresh, G., Sateesh, A., Singh, S. K., Pérez-Campos, X., Suresh, G., Koketsu, K., Masuda, T., Domen, K., and Ito, T. CIGN, A Strong-Motion Seismic Network in Central Indo-Gangetic Plains, Foothills of Himalayas: First Results. *Seismological Research Letters*, 87(1):37–46, Dec. 2015. doi: 10.1785/0220150106.

Chiou, B. S.-J. and Youngs, R. R. Update of the Chiou and Youngs NGA model for the average horizontal component of peak ground motion and response spectra. *Earthquake Spectra*, 30(3):1117–1153, 2014.

Cong, Z., Nejat, A., Liang, D., Pei, Y., and Javid, R. J. Individual relocation decisions after tornadoes: a multi-level analysis. *Disasters*, 42(2):233–250, 2018. doi: 10.1111/disa.12241.

Costa, R., Haukaas, T., and Chang, S. E. Predicting population displacements after earthquakes. *Sustainable and Resilient Infrastructure*, 7(4):253–271, July 2022. doi: 10.1080/23789689.2020.1746047.

Cremen, G., Galasso, C., and McCloskey, J. A Simulation-Based Framework for Earthquake Risk-Informed and People-Centered Decision Making on Future Urban Planning. *Earth's Future*, 10 (1):e2021EF002388, Jan. 2022. doi: 10.1029/2021EF002388.

Crowley, H., Silva, V., Kalakonas, P., Martins, L., Weatherill, G., Pitilakis, K., Riga, E., Borzi, B., and Faravelli, M. Verification of the European seismic risk model (ESRM20). In *Proceedings of the 17th world conference on earthquake engineering, Sendai, Japan*, volume 27, 2020. https://wcee.nicee.org/wcee/article/17WCEE/8b-0045.pdf.

DeWaard, J., Johnson, J., and Whitaker, S. Internal migration in the United States: A comprehensive comparative assessment of the Consumer Credit Panel. *Demographic Research*, 41:953–1006, Oct. 2019. doi: 10.4054/DemRes.2019.41.33.

DeWaard, J., Johnson, J. E., and Whitaker, S. D. Out-migration from and return migration to Puerto Rico after Hurricane Maria: evidence from the consumer credit panel. *Population and Environment*, 42(1):28–42, Sept. 2020. doi: 10.1007/s11111-020-00339-5.

Elliott, J. R. and Pais, J. Race, class, and Hurricane Katrina: Social differences in human responses to disaster. *Social Science Research*, 35(2):295–321, June 2006. doi: 10.1016/j.ssresearch.2006.02.003.

Engler, D. T., Worden, C. B., Thompson, E. M., and Jaiswal, K. S. Partitioning Ground Motion Uncertainty When Conditioned on Station Data. *Bulletin of the Seismological Society of America*, 112(2):1060–1079, Jan. 2022. doi: 10.1785/0120210177.

Esnard, A.-M. and Sapat, A. *Displaced by Disaster: Recovery and Resilience in a Globalizing World*. Routledge, New York, July 2014. doi: 10.4324/9780203728291.

FlowMinder. Haiti: Earthquake on 14 August 2021 (Version 1.2). Technical report, Aug. 2021. https://www.flowminder.org/media/dpxfefl4/haitiearthquake_report_27-aug_report-2_eng_v1-2_final.pdf.

Frias-Martinez, V. and Virseda, J. On the relationship between socio-economic factors and cell phone usage. In *Proceedings of the Fifth International Conference on Information and Communication Technologies and Development*, ICTD '12, pages 76–84, New York, NY, USA, Mar. 2012. Association for Computing Machinery. doi: 10.1145/2160673.2160684.

Greer, A. *Household residential decision-making in the wake of disaster: cases from Hurricane Sandy*. PhD thesis, University of Delaware, 2015. https://udspace.udel.edu/handle/19716/31364.

Grinberger, A. Y. and Felsenstein, D. Dynamic agent based simulation of welfare effects of urban disasters. *Computers, Environment and Urban Systems*, 59:129–141, Sept. 2016. doi: 10.1016/j.compenvurbsys.2016.06.005.

Groen, J. A. and Polivka, A. E. Going home after Hurricane Katrina: Determinants of return migration and changes in affected areas. *Demography*, 47(4):821–844, 2010.

Grünthal, G. European macroseismic scale 1998 (EMS-98). 1998. https://gfzpublic.gfz-potsdam.de/rest/items/item_227033_2/component/file_227032/content.

Guadagno, L. and Yonetani, M. Displacement risk: Unpacking a problematic concept for disaster risk reduction. *International Migration*, 61(5):13–28, 2023. doi: 10.1111/imig.13004.

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., and Beaudet, C. From Poverty to Disaster and Back: a Review of the Literature. *Economics of Disasters and Climate Change*, 4(1): 223–247, Apr. 2020. doi: 10.1007/s41885-020-00060-5.

Hayes, G. P., Briggs, R. W., Barnhart, W. D., Yeck, W. L., McNamara, D. E., Wald, D. J., Nealy, J. L., Benz, H. M., Gold, R. D., and Jaiswal, K. S. Rapid characterization of the 2015 M w 7.8 Gorkha, Nepal, earthquake sequence and its seismotectonic context. *Seismological Research Letters*, 86(6):1557–1567, 2015.

Heath, D. C., Wald, D. J., Worden, C. B., Thompson, E. M., and Smoczyk, G. M. A global hybrid VS 30 map with a topographic slope – based default and regional map insets. *Earthquake Spectra*, 36(3):1570–1584, 2020.

Hinojosa, J. Two Sides of the Coin of Puerto Rican Migration: Depopulation in Puerto Rico and the Redefinition of the Diaspora. *Centro Journal*, 30(3), 2018. https://www.academia.edu/download/59765896/J.HINOJOSA_CENTROJOURNAL-FALL2018.pdf.

Hinojosa, J. and Meléndez, E. Puerto Rican Exodus: One Year Since Hurricane Maria. Technical Report Centro RB2018-05, Centro Library and Archives, New York, NY, USA, Sept. 2018.

Hough, S. E., Martin, S. S., Gahalaut, V., Joshi, A., Landes, M., and Bossu, R. A comparison of observed and predicted ground motions from the 2015 MW7.8 Gorkha, Nepal, earthquake. *Natural Hazards*, 84(3):1661–1684, Dec. 2016. doi: 10.1007/s11069-016-2505-8.

Hoyos, M. C. and Silva, V. Exploring benefit cost analysis to support earthquake risk mitigation in Central America. *International Journal of Disaster Risk Reduction*, 80:103162, 2022. doi: https://doi.org/10.1016/j.ijdrr.2022.103162.

ICIMOD. Lessons from Nepal's Gorkha earthquake 2015. Technical report, Kathmandu, Nepal, 2015.

IDMC. Global Internal Displacement Database. https://www.internal-displacement.org/database.

IDMC. GRID Methodological Annex. Technical report, 2018. https://www.internal-displacement.org/global-report/grid2018/downloads/report/2018-GRID-methodological-annex.pdf.

IDMC. Disaster Displacement - A global review, 2008-2018. Technical report, 2019. https://www.internal-displacement.org/publications/disaster-displacement-a-global-review.

IDMC. GRID Methodology. Technical report, 2020. https://www.internal-displacement.org/global-report/grid2020/downloads/2020-IDMC-GRID-methodology.pdf.

IDMC. Urban case study: Ba Town, Fiji. Technical report, July 2022a. https://www.internal-displacement.org/publications/pacific-response-to-disaster-displacement-urban-case-study-ba-town-fiji/.

IDMC. Urban case study: Port Vila, Vanuatu. Technical report, July 2022b. https://www.internal-displacement.org/publications/pacific-response-to-disaster-displacement-urban-case-study-port-vila-vanuatu/.

JCO. Disaster Report for 2016 Kumamoto earthquake. Technical report, Apr. 2017. https://www.bousai.go.jp/updates/h280414jishin/pdf/h280414jishin_39.pdf.

Kalakonas, P., Silva, V., Mouyiannou, A., and Rao, A. Exploring the impact of epistemic uncertainty on a regional probabilistic seismic risk assessment model. *Natural Hazards*, 104(1):997–1020, 2020. doi: https://doi.org/10.1007/s11069-020-04201-7.

Kolbe, A. R., Hutson, R. A., Shannon, H., Trzcinski, E., Miles, B., Levitz, N., Puccio, M., James, L., Noel, J. R., and Muggah, R. Mortality, crime and access to basic needs before and after the Haiti earthquake: a random survey of Port-au-Prince households. *Medicine, Conflict and Survival*, 26(4):281–297, Oct. 2010. doi: 10.1080/13623699.2010.535279.

Lee, C.-C., Chou, C., and Mostafavi, A. Specifying Evacuation Return and Home-switch Stability During Short-term Disaster Recovery Using Location-based Data. *Scientific Reports*, 12(1):15987, Sept. 2022. doi: 10.1038/s41598-022-20384-4.

Lee, Y.-J., Sugiura, H., and Gečienė, I. Stay or Relocate: The Roles of Networks After the Great East Japan Earthquake. In Jones, E. C. and Faas, A. J., editors, *Social Network Analysis of Disaster Response, Recovery, and Adaptation*, pages 223–238. Butterworth-Heinemann, Jan. 2017. doi: 10.1016/B978-0-12-805196-2.00015-7.

Liel, A. B. and Deierlein, G. G. Cost-Benefit Evaluation of Seismic Risk Mitigation Alternatives for Older Concrete Frame Buildings. *Earthquake Spectra*, 29(4):1391–1411, Nov. 2013. doi: 10.1193/030911EQS040M.

Lin, Y.-S. *Development of algorithms to estimate post-disaster population dislocation—a research-based approach*. Texas A&M University, 2009.

Lines, R., Faure Walker, J. P., and Yore, R. Progression through emergency and temporary shelter, transitional housing and permanent housing: A longitudinal case study from the 2018 Lombok earthquake, Indonesia. *International Journal of Disaster Risk Reduction*, 75:102959, June 2022. doi: 10.1016/j.ijdrr.2022.102959.

Loos, S., Lallemant, D., Baker, J., McCaughey, J., Yun, S.-H., Budhathoki, N., Khan, F., and Singh, R. G-DIF: A geospatial data integration framework to rapidly estimate post-earthquake damage. *Earthquake Spectra*, 36(4):1695–1718, Nov. 2020. doi: 10.1177/8755293020926190.

Loos, S., Lallemant, D., Khan, F., McCaughey, J. W., Banick, R., Budhathoki, N., and Baker, J. W. A data-driven approach to rapidly estimate recovery potential to go beyond building damage after disasters. *Communications Earth & Environment*, 4(1):1–12, Feb. 2023. doi: 10.1038/s43247-023-00699-4.

Love, T. Population movement after natural disasters: a literature review and assessment of Christchurch data. Technical report, Sapere Research Group, Wellington, New Zealand, 2011.

Lu, X., Bengtsson, L., and Holme, P. Predictability of population displacement after the 2010 Haiti earthquake. *Proceedings of the National Academy of Sciences*, 109(29):11576–11581, July 2012. doi: 10.1073/pnas.1203882109.

Martins, L. and Silva, V. Development of a fragility and vulnerability model for global seismic risk analyses. *Bulletin of Earthquake Engineering*, 19(15):6719–6745, Dec. 2021. doi: 10.1007/s10518-020-00885-1.

Mayer, J., Moradi, S., Nejat, A., Ghosh, S., Cong, Z., and Liang, D. Drivers of post-disaster relocations: The case of Moore and Hattiesburg tornados. *International Journal of Disaster Risk Reduction*, 49:101643, Oct. 2020. doi: 10.1016/j.ijdrr.2020.101643.

McAdam, J. Evacuations: a form of disaster displacement? *Forced Migration Review*, (69):56–57, 2022. https://www.proquest.com/docview/2647725690/abstract/DB0755D2F79B4311PQ/1.

Milusheva, S., Bjorkegren, D., and Viotti, L. Assessing Bias in Smartphone Mobility Estimates in Low Income Countries. In *ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS)*, pages 364–378, Virtual Event Australia, June 2021. ACM. doi: 10.1145/3460112.3471968.

Nawrotzki, R. J., Brenkert-Smith, H., Hunter, L. M., and Champ, P. A. Wildfire-Migration Dynamics: Lessons from Colorado's Fourmile Canyon Fire. *Society & Natural Resources*, 27(2):215–225, Feb. 2014. doi: 10.1080/08941920.2013.842275.

Nejat, A. and Ghosh, S. LASSO Model of Postdisaster Housing Recovery: Case Study of Hurricane Sandy. *Natural Hazards Review*, 17(3):04016007, Aug. 2016. doi: 10.1061/(ASCE)NH.1527-6996.0000223.

Newell, J., Beaven, S., and Johnston, D. M. Population movements following the 2010-2011 Canterbury Earthquakes: Summary of research workshops November 2011 and current evidence. Technical report, 2012.

Newzoo. Global Mobile Market Report 2017. Technical report, Apr. 2017. https://newzoo.com/resources/trend-reports/global-mobile-market-report-light-2017.

Paul, N., Galasso, C., and Baker, J. Household Displacement and Return in Disasters: A Review. *Natural Hazards Review*, 25(1):03123006, Feb. 2024. doi: 10.1061/NHREFO.NHENG-1930.

Plyer, A., Bonaguro, J., and Hodges, K. Using administrative data to estimate population displacement and resettlement following a catastrophic U.S. disaster. *Population and Environment*, 31(1):150–175, Jan. 2010. doi: 10.1007/s11111-009-0091-3.

Price, D. Population and household trends in Christchurch post February 22 earthquake. In *Population and Employment Effects of the Christchurch Earthquakes workshop*, 2011.

Quarantelli, E. L. General and particular observations on sheltering and housing in American disasters. *Disasters*, 6(4):277–281, 1982. doi: 10.1111/j.1467-7717.1982.tb00550.x.

Quarantelli, E. L. Patterns of sheltering and housing in US disasters. *Disaster Prevention and Management: An International Journal*, 4(3):43–53, Jan. 1995. doi: 10.1108/09653569510088069.

Rajaure, S., Asimaki, D., Thompson, E. M., Hough, S., Martin, S., Ampuero, J. P., Dhital, M. R., Inbal, A., Takai, N., Shigefuji, M., Bijukchhen, S., Ichiyanagi, M., Sasatani, T., and Paudel, L. Characterizing the Kathmandu Valley sediment response through strong motion recordings of the 2015 Gorkha earthquake sequence. *Tectonophysics*, 714-715:146–157, Sept. 2017. doi: 10.1016/j.tecto.2016.09.030.

Sharygin, E. Estimating Migration Impacts of Wildfire: California's 2017 North Bay Fires. In Karácsonyi, D., Taylor, A., and Bird, D., editors, *The Demography of Disasters: Impacts for Population and Place*, pages 49–70. Springer International Publishing, Cham, 2021. doi: 10.1007/978-3-030-49920-4_3.

Silva, V. Critical Issues in Earthquake Scenario Loss Modeling. *Journal of Earthquake Engineering*, 20(8):1322–1341, Nov. 2016. doi: 10.1080/13632469.2016.1138172.

Silva, V. Critical Issues on Probabilistic Earthquake Loss Assessment. *Journal of Earthquake Engineering*, 22(9):1683–1709, Oct. 2018. doi: 10.1080/13632469.2017.1297264.

Silva, V. and Horspool, N. Combining USGS ShakeMaps and the OpenQuake-engine for damage and loss assessment. *Earth-*

quake Engineering & Structural Dynamics, 48(6):634–652, 2019. doi: 10.1002/eqe.3154.

Silva, V., Crowley, H., Pagani, M., Monelli, D., and Pinho, R. Development of the OpenQuake engine, the Global Earthquake Model' s open-source software for seismic risk assessment. *Natural Hazards*, 72:1409–1427, 2014.

Silva, V., Amo-Oduro, D., Calderon, A., Costa, C., Dabbeek, J., Despotaki, V., Martins, L., Pagani, M., Rao, A., and Simionato, M. Development of a global seismic risk model. *Earthquake Spectra*, 36(1_suppl):372–394, 2020.

The Asia Foundation. Independent Impacts and Recovery Monitoring Phase Five. Technical report, The Asia Foundation, San Francisco, CA, USA, 2019. https://asiafoundation.org/wp-content/uploads/2021/03/IRM-Nepal_Aid-and-Recovery-in-Post-Earthquake-Nepal-Qualititative-Field-MonitoringNovember-2019_EN.pdf.

Van De Lindt, J. W., Peacock, W. G., Mitrani-Reiser, J., Rosenheim, N., Deniz, D., Dillard, M., Tomiczek, T., Koliou, M., Graettinger, A., Crawford, P. S., Harrison, K., Barbosa, A., Tobin, J., Helgeson, J., Peek, L., Memari, M., Sutley, E. J., Hamideh, S., Gu, D., Cauffman, S., and Fung, J. Community Resilience-Focused Technical Investigation of the 2016 Lumberton, North Carolina, Flood: An Interdisciplinary Approach. *Natural Hazards Review*, 21(3):04020029, Aug. 2020. doi: 10.1061/(ASCE)NH.1527-6996.0000387.

Ward, P. J., Blauhut, V., Bloemendaal, N., Daniell, J. E., de Ruiter, M. C., Duncan, M. J., Emberson, R., Jenkins, S. F., Kirschbaum, D., Kunz, M., Mohr, S., Muis, S., Riddell, G. A., Schäfer, A., Stanley, T., Veldkamp, T. I. E., and Winsemius, H. C. Review article: Natural hazard risk assessments at the global scale. *Natural Hazards and Earth System Sciences*, 20(4):1069–1096, Apr. 2020. doi: 10.5194/nhess-20-1069-2020.

Wesolowski, A., Eagle, N., Noor, A. M., Snow, R. W., and Buckee, C. O. Heterogeneous Mobile Phone Ownership and Usage Patterns in Kenya. *PLoS ONE*, 7(4):e35319, Apr. 2012. doi: 10.1371/journal.pone.0035319.

Wesolowski, A., Eagle, N., Noor, A. M., Snow, R. W., and Buckee, C. O. The impact of biases in mobile phone ownership on estimates of human mobility. *Journal of The Royal Society Interface*, 10(81):20120986, Apr. 2013. doi: 10.1098/rsif.2012.0986.

Wilson, R., zu Erbach-Schoenberg, E., Albert, M., Power, D., Tudge, S., Gonzalez, M., Guthrie, S., Chamberlain, H., Brooks, C., Hughes, C., Pitonakova, L., Buckee, C., Lu, X., Wetter, E., Tatem, A., and Bengtsson, L. Rapid and Near Real-Time Assessments of Population Displacement Using Mobile Phone Data Following Disasters: The 2015 Nepal Earthquake. *PLoS Currents*, 8:ecurrents.dis.d073fbece328e4c39087bc086d694b5c, Feb. 2016. doi: 10.1371/currents.dis.d073fbece328e4c39087bc086d694b5c.

World Bank Group. Mobile cellular subscriptions (per 100 people), 2021. https://data.worldbank.org.

Yabe, T., Sekimoto, Y., Tsubouchi, K., and Ikemoto, S. Cross-comparative analysis of evacuation behavior after earthquakes using mobile phone data. *PLOS ONE*, 14(2):e0211375, Feb. 2019. doi: 10.1371/journal.pone.0211375.

Yabe, T., Tsubouchi, K., Fujiwara, N., Sekimoto, Y., and Ukkusuri, S. V. Understanding post-disaster population recovery patterns. *Journal of The Royal Society Interface*, 17(163):20190532, Feb. 2020. doi: 10.1098/rsif.2019.0532.

Yabe, T., Jones, N. K. W., Lozano-Gracia, N., Khan, M. F., Ukkusuri, S. V., Fraiberger, S., and Montfort, A. Location Data Reveals Disproportionate Disaster Impact Amongst the Poor: A Case Study of the 2017 Puebla Earthquake Using Mobilkit, July 2021. doi: 10.48550/arXiv.2107.13590.

Yabe, T., Jones, N. K. W., Rao, P. S. C., Gonzalez, M. C., and Ukkusuri, S. V. Mobile phone location data for disasters: A review from natural hazards and epidemics. *Computers, Environment and Urban Systems*, 94:101777, June 2022. doi: 10.1016/j.compenvurbsys.2022.101777.

Yepes-Estrada, C., Calderon, A., Costa, C., Crowley, H., Dabbeek, J., Hoyos, M. C., Martins, L., Paul, N., Rao, A., and Silva, V. Global building exposure model for earthquake risk assessment. *Earthquake Spectra*, 39(4):2212–2235, Nov. 2023. doi: 10.1177/87552930231194048.