SECED 2023 Conference
Earthquake Engineering & Dynamics for a Sustainable Future
14-15 September 2023, Cambridge, UK

BENCHMARKING HOUSING DAMAGE AS A DRIVER OF POPULATION DISPLACEMENT FOLLOWING EARTHQUAKES

Nicole PAUL[1,2], Carmine GALASSO[3], Vitor SILVA[4,5] & Jack BAKER[6]

Abstract: *In the aftermath of an earthquake, the number of occupants within destroyed housing is often used to approximate the number of people rendered homeless after the event. While this metric can provide rapid situational awareness, more recent research highlights the importance of additional factors beyond housing damage within the scope of household displacement (e.g., utility disruption, housing tenure, place attachment). This study models three recent earthquakes from different geographies (Haiti, Japan, and Nepal) to benchmark housing damage as a driver of population displacement against reported values and mobile location data-based estimates. The results highlight the promise of risk models to realistically estimate population displacement after earthquakes in the emergency phase as compared with official reports, but also indicate a large range of uncertainty in the predicted values. Furthermore, purely basing displacement estimates on housing damage may limit the ability of models to capture protracted displacement compared to more comprehensive models that include other factors influencing population return or alternative approaches such as using mobile location data. Although mobile location data offers potential to quantify displacement duration, the results of this study indicate further need to benchmark and validate such approaches.*

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. Despite this scale of human impact, most disaster risk assessments have focused on economic losses and casualties. More recent studies have aimed to quantify population displacement following earthquakes (Grinberger and Felsenstein, 2016; Burton *et al.*, 2019; Bhattacharya and Kato, 2021; Costa, Haukaas and Chang, 2022), identifying a range of influencing factors. Numerous potential determinants of population displacement have been identified (e.g., homeownership, place attachment, utility disruption); yet, standard practice is simply to multiply the number of destroyed (i.e., uninhabitable) housing units by the average household size. Regardless of the selected risk metric, an issue that plagues disaster risk assessment is the need for more benchmarking or validation studies to ensure that risk models reasonably predict observed values. This study aims to benchmark the standard practice of using housing destruction as a driver of displacement against official statistics and alternative estimates using mobile location data, allowing us to understand the prediction potential and uncertainty range of this simplified approach.

[1] PhD Candidate, University College London, London, UK, nicole.paul.22@ucl.ac.uk
[2] Risk Analyst, Global Earthquake Model Foundation, Pavia, Italy
[3] Professor, University College London, London, UK
[4] Risk Coordinator, Global Earthquake Model Foundation, Pavia, Italy
[5] Professor, University Fernando Pessoa, Porto, Portugal
[6] Professor, Stanford University, Stanford, USA

Approaches to quantifying population displacement

Defining population displacement

Past researchers have highlighted a lack of consistent terminology regarding population displacement in the disaster context (e.g., Mitchell, Esnard and Sapat, 2012; Esnard and Sapat, 2014; Greer, 2015), which has complicated 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 metrics associated with displacement after disaster events, including evacuations (i.e., people leaving their habitual residence in advance of or during the onset of a hazard), sheltered populations (i.e., people accommodated in shelters or relief camps provided by national authorities or other organizations), and the population rendered homeless (i.e., due to housing destruction; IDMC, no date). As discussed in IDMC (2018), evacuation estimates are based on the population covered by mandatory evacuation orders and/or the population in shelters. In contrast, estimates of the homeless population are primarily based on housing destruction estimates, typically multiplied by the average household size. This metric is most similar to the majority of past attempts to quantify displacement (or "dislocation"; Lin, 2009) within the earthquake engineering discipline; that is, damage incurred by an earthquake render dwellings uninhabitable, thereby displacing residents.

Although physical damage to housing has often been considered a primary driver of initial displacement (i.e., in the emergency phases), more recent studies have highlighted the importance of additional factors beyond housing damage (e.g., Henry, 2013; Costa, Haukaas and Chang, 2022). In particular, household decisions to permanently (and voluntarily) relocate (i.e., resettle) after disasters may be affected by factors such as place attachment (e.g., Costa, Wang and Baker, 2022), social networks or social capital (e.g., Nejat and Damnjanovic, 2012; Nejat, Cong and Liang, 2016; Lee, Sugiura and Gečienė, 2017), and home ownership (e.g., Kim and Oh, 2014; Mayer *et al.*, 2020). Despite the importance of population return, the benchmarking study presented in this paper is limited to initial displacement estimates, which may inform shelter needs in the emergency phase.

Approaches to quantifying population 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 may seek public shelter. While headcounts of sheltered populations can be relatively straightforward, evidence from past events indicates that only a small subset of the displaced population seeks public shelters (Quarantelli, 1982), and data regarding those that seek accommodation elsewhere is difficult to ascertain. As such, a variety of approaches have been undertaken to estimate population displacement following disasters:

- Based on housing destruction estimates: Reported or modelled estimates of housing destruction are multiplied by the household size to determine the population rendered homeless. This is the standard practice used by the IDMC to determine many of its displacement estimates (IDMC, 2018).
- Based on household surveys: A sample of households that habitually resided in an affected area can be surveyed to understand the proportion that continues to be away from home, ever evacuated, or ever sought public shelter. However, it can be challenging to contact displaced populations. As an example of this approach, Kolbe *et al.* (2010) estimated that 1,269,110 people were still displaced 1-2 months after the 2010 Haiti earthquake, and 79,213 people sought shelter.
- Manual counting of movements: Population movements can be estimated by tracking data such as bus and ship movements out of an affected area, as the Haitian National Civil Protection Agency (NPCA) performed following the 2010 Haiti earthquake. According to their estimates, 511,405 people left Port-au-Prince about three weeks after the earthquake (Bengtsson *et al.*, 2011).
- Mobile location data-based estimates: Call detail records (CDRs) or smartphone GPS location data can be used to track population movements following disaster events (Yabe *et al.*, 2022). For example, Bengtsson *et al.* (2011) used CDRs to estimate that 580,000 people left Port-au-Prince about three weeks after the 2010 Haiti earthquake.

In this study, a model-based approach using housing destruction estimates is benchmarked against other available estimates for recent earthquake events. For the considered events, only estimates based on reported housing destruction estimates (from official statistics or IDMC) and estimates from mobile location data (from the literature) were available. While the model-based estimates in this study follow the same underlying assumption as the reported figures from official statistics or the IDMC (i.e., based on housing destruction), the housing damage is simulated based on the earthquake rupture characteristics, resulting ground shaking local intensity estimates, and any available seismic station data 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). As such, the results from the benchmarking study allow us to evaluate the prediction potential and uncertainty range of earthquake risk models. Such models might be used to assess disaster risk potential in terms of population displacement (together with other risk metrics) for future events and evaluate the cost-benefit of potential mitigation strategies.

Past earthquake scenario risk models

Selected scenarios

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

- Recency: The exposure model used herein is representative of the year 2021. Therefore, the modelled populations may not represent past decades, particularly if there has been significant population growth or decline in recent years.
- Availability of mobile location data-based estimates: 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.

Earthquake	**Date**	**Country**
2021 M_W7.2 Nippes	2021 August 14	Haiti
2016 M_W7.0 Kumamoto	2016 April 16	Japan
2015 M_W7.8 Gorkha	2015 April 25	Nepal

Table 1. Selected earthquake scenarios for the benchmarking study.

Data collection and input models

Two primary data sources were used to derive the scenario risk 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 (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 available online at: https://github.com/gem/earthquake-scenarios. For this study, ground shaking estimates from seismic stations, rupture model definitions, and candidate GMMs were taken from this repository to develop the hazard model component. Table 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 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).

Earthquake	**Seismic stations**	**Rupture model**	**Selected GMM**
2021 M_W7.2 Nippes	USGS[1] (us6000f65h)	USGS finite fault model (us6000f65h)	Akkar, Sandıkkaya and

			Bommer, (2014)
2016 M_W7.0 Kumamoto	USGS[1] (us20005iis) NIED[2]	USGS fault rupture model (us20005iis)	Chiou and Youngs, (2014)
2015 M_W7.8 Gorkha	USGS[1] (us20002926) CESMD[3] Bhattarai *et al.* (2015)	Hayes *et al.*, (2015)	Atkinson and Boore, (2003)

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

This benchmarking study also used model components from GEM's current 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) were directly used. The exposure models include building counts, the number of occupants, and building typologies, which are based primarily on national statistics but are 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 different damage states: slight, moderate, extensive, and complete damage. Further documentation on the fragility derivation process can be found at: https://docs.openquake.org/vulnerability/. For this benchmarking study, it was assumed that all occupants within extensively and completely damaged buildings would be rendered homeless. That is, dwellings in the extensive or complete damage state were assumed to be "uninhabitable," thereby displacing their occupants.

Scenario risk analysis methodology

The scenario risk analyses were performed using the OpenQuake Engine (OQ; Silva *et al.*, 2014), an open-source seismic hazard and risk analysis software. Recently, 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). For this study, 1,000 Monte Carlo samples of cross-spatially correlated ground motions conditioned on available seismic station data were generated for each event. 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 realized 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.

Benchmarking results

Selected metrics for comparison

The metrics for this benchmarking study include housing damage counts, housing destruction counts, and multiple 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 identifies the following building damage states: partially damaged (一部破損), partially destroyed (半壊), and completely destroyed (全壊). To facilitate comparison, the different reported damage states were summed into the categories "damaged" and "destroyed," where destroyed dwellings are considered uninhabitable and damaged buildings suffered some damage (but are not destroyed). The assumed mapping is shown in Table 3.

Country	Source	Damaged housing	Destroyed housing
All	This study (OQ)	Slight Moderate	Extensive Complete
Haiti	Caribbean Disaster Emergency Management Agency (2021)	Damaged	Destroyed

Japan	Japan Cabinet Office (2017)	Partially damaged (一部破損)	Partially destroyed (半壊) Completely destroyed (全壊)
Nepal	International Centre for Integrated Mountain Development (2015)	Partially damaged	Fully damaged

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

Similarly, different sources report displacement figures using a different basis for the metric (i.e., rendered homeless, sheltered, evacuated). Unlike damage, it is not realistic to sum the various metrics to get an aggregate metric, 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 can also vary for mobile location data-based displacement estimates, which is summarized in Table 4 for the referenced studies.

Country	**Source**	**Criteria for displacement**
Haiti	FlowMinder (2021)	"moved from their pre-earthquake usual locations" within the Grand'Anse, Sud, and Nippes departments during the first week after the earthquake
Japan	Yabe *et al.* (2020)	"the rate of affected users who stayed outside their home [shichoson (cities/wards)] out of all affected users on that day" on the day of the earthquake
Nepal	Wilson *et al.* (2016)	"people above normal levels had left the [Kathmandu] valley" in the first three weeks after the earthquake

Table 4. Criteria used to estimate displacement based on mobile location data.

Haiti's 2021 M_W 7.2 Nippes earthquake

A comparison of the results for the 2021 Nippes earthquake is shown in Table 5 and Figure 1. For this event, the scenario model predicted similar average damage estimates (and therefore similar average displacement estimates) to official reports and the 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). Additionally, the mobile location data-based estimates assume that movement of the sample population (i.e., 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. Although all estimates are within the modelled distribution, the range of values is significant (~100,000 to ~350,000 displaced).

	Risk model	Reported		Mobile data
	This study (OQ)	Caribbean Disaster Emergency Management Agency (2021)	IDMC (no date)	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 5. Comparison of results for the 2021 M_W7.2 Nippes earthquake in Haiti; "n. r." indicates the value was not reported in that source.

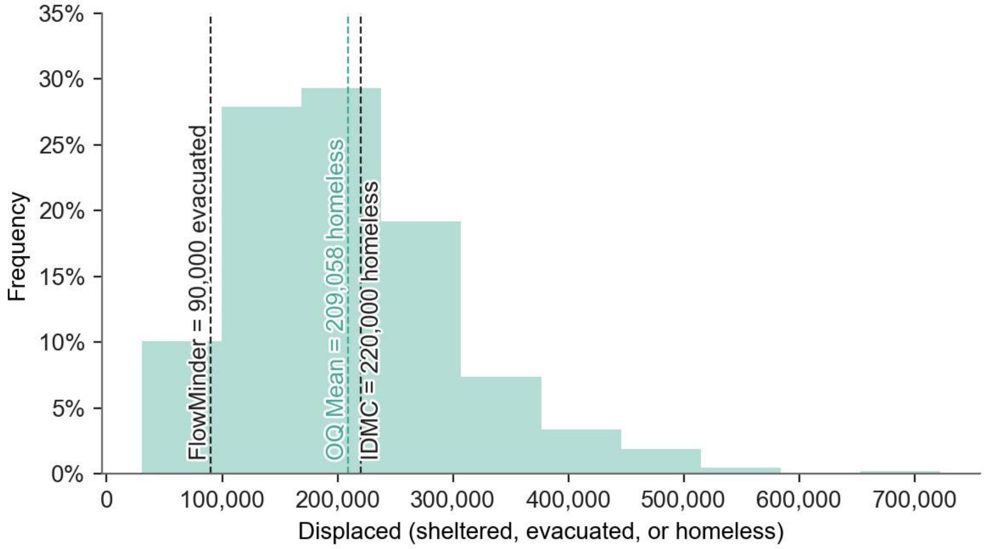

Figure 1. The modelled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2021 MW7.2 Nippes earthquake in Haiti.

Japan's 2016 M_W 7.0 Kumamoto earthquake

The comparison of results for the 2016 Kumamoto earthquake is shown in Table 6 and Figure 2. For this event, the scenario model again predicted similar average damage and displacement estimates to the reported data. However, there was a notable discrepancy between the average buildings estimated in complete damage in OQ and reported as completely destroyed by the official statistics. 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, whereby residents who evacuate seek public shelter only as a last resort (Quarantelli, 1982). In this case, the mobile location databased estimate exceeds the modelled and reported estimates but is of a similar magnitude. All estimates are well within the range of the modelled distribution. The range of values predicted by the model (~100,000 to ~300,000) has a similar but slightly smaller range than in the 2021 Nippes earthquake in Haiti.

	Risk model	Reported		Mobile data
	This study (OQ)	Japan Cabinet Office (2017)	IDMC (no date)	Yabe *et al.* (2020)*
Damaged houses	**150,072**	**155,902**	**n. r.**	**n. r.**
Slight	104,502	n. r.	n. r.	n. r.
Moderate	45,570	n. r.	n. r.	n. r.
Destroyed houses	**65,066**	**42,716**	**n. r.**	**n. r.**
Extensive	23,911	34,037	n. r.	n. r.
Complete	41,155	8,679	n. r.	n. r.
Displaced	**218,708**	**196,325**	**196,300**	**308,422**
Sheltered	n. r.	196,325	196,300	n. r.
Evacuated	n. r.	1,224	n. r.	308,422
Homeless	218,708	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 earthquake); 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 6. Comparison of results for the 2016 M_W7.0 Kumamoto earthquake in Japan; "n. r." indicates the value was not reported in that source.

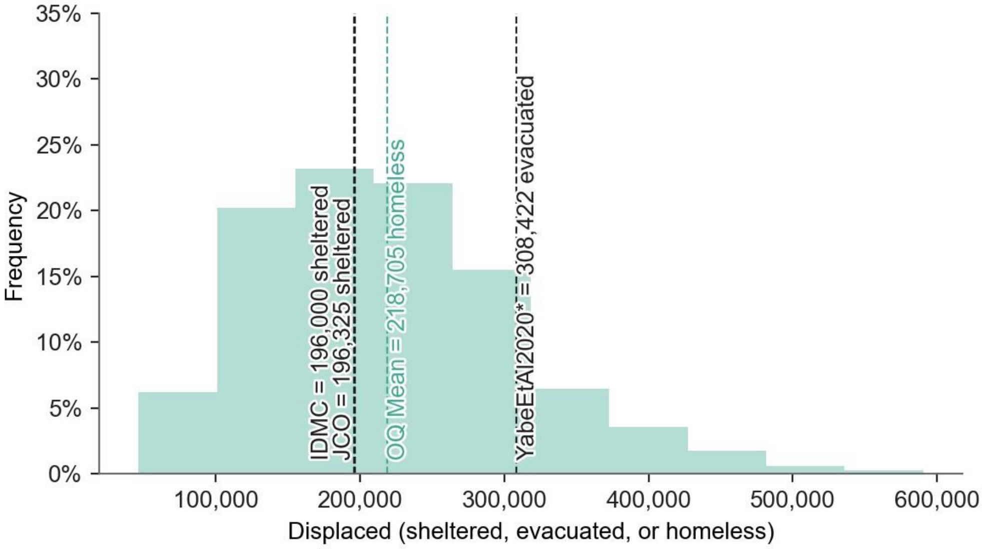

Figure 2. The modelled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2016 M_W7.0 Kumamoto earthquake in Japan.

Nepal's 2015 M_W 7.8 Gorkha earthquake

The comparison of results for the 2015 Gorkha earthquake in Nepal is shown in Table 7 and Figure 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. For this reason, 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 modelled and reported estimates, although this could be due to the criteria employed within that study ("people above normal levels had left the [Kathmandu] valley" in the first few weeks after the earthquake). Under that criterion, individuals that 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. Once again, all estimates lie within the modelled distribution. However, the range of predicted values (~800,000 to ~3,000,000) 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.

	Risk model	Reported		Mobile data
	This study (OQ)	International Centre for Integrated Mountain Development (2015)	IDMC (no date)	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.

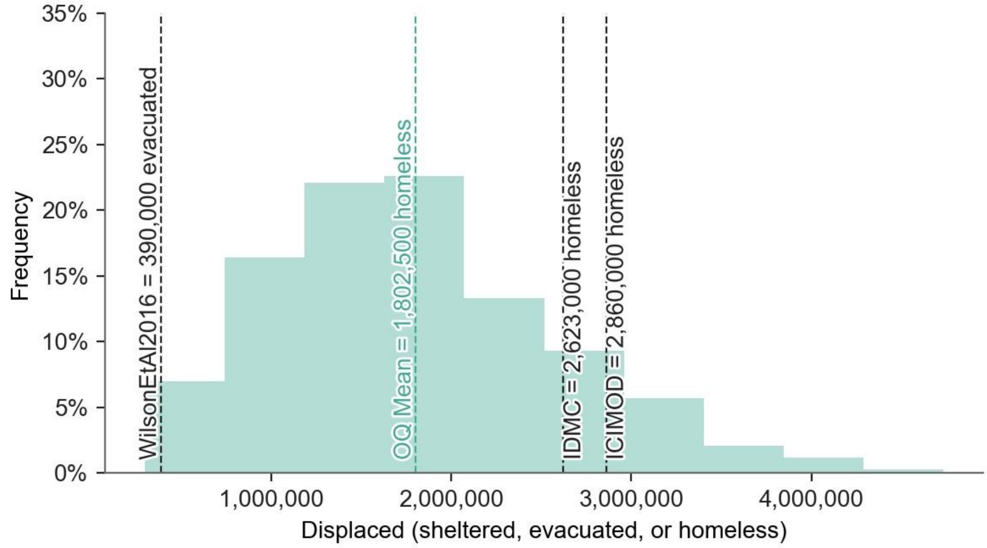

Figure 3. The modelled distribution of population displaced in this study (OQ) relative to other benchmarks for the 2015 M_W7.8 Gorkha earthquake in Nepal.

Conclusion

This study compared displacement predictions based on residential damage estimates from earthquake risk models against official statistics and mobile location data-based estimates. The model results seem promising as they are all broadly consistent with alternative estimates, but there is a notable uncertainty range in all considered earthquake scenarios. Additionally, the official statistics typically are 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, validation is complicated by the use of many different metrics to quantify displaced populations (i.e., rendered homeless, sheltered, evacuated).

The mobile location data-based estimates offer an interesting comparison, but further evaluation of the displacement criteria used and the representativeness of the sample population may be required. In the case of the Haiti and Nepal earthquakes, the mobile location data-based estimates were notably lower than the mobel-based estimates and official reports. In some cases, this may be because the considered population was restricted to specific areas (e.g., within the Kathmandu Valley) or that there was an insufficient spatial resolution used in the displacement criteria (i.e., neglecting those who left their habitual residence but migrated short distances). Another issue could be that the movements of the sample population (i.e., those with phones) are not fully representative of the affected population (e.g., elderly populations may be less likely to carry phones and may also inhabit older buildings more prone to damage). Although more study is needed, mobile location data offers the potential to explicitly capture the space and time components of displacement.

In this study, the housing destruction-based estimates yielded reasonable estimates as compared with the official reports. While this is a promising result for rapid estimates using the standard practice, some critical factors that influence population displacement and shelter-seeking behavior are neglected (e.g., utility disruption, weather). Moreover, quantification of the duration of displacement remains a challenge as critical factors influencing population return in the recovery phase (e.g., home ownership, place attachment, social networks) are not considered.

The results from this benchmarking study demonstrate the potential use of disaster risk models to evaluate population displacement in the emergency phase, which can be useful for real-time predictions to rapidly estimate shelter needs or can help expand the metrics quantified within “what-if” scenarios and cost-benefit studies to capture more equitable and people-centered metrics beyond economic loss and casualties.

References

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

Atkinson, G.M. and Boore, D.M. (2003) ‘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), pp. 1703–1729.

Bengtsson, L. et al. (2011) ‘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), p. e1001083. Available at: https://doi.org/10.1371/journal.pmed.1001083.

Bhattacharya, Y. and Kato, T. (2021) ‘Development of an Agent-Based Model on the Decision-Making of Dislocated People After Disasters’, in S.C.M. Geertman et al. (eds) Urban Informatics and Future Cities. Cham: Springer International Publishing (The Urban Book Series), pp. 387–406. Available at: https://doi.org/10.1007/978-3-030-76059-5_20.

Bhattarai, M. et al. (2015) ‘Overview of the large 25 April 2015 Gorkha, Nepal, earthquake from accelerometric perspectives’, Seismological Research Letters, 86(6), pp. 1540–1548.

Burton, H. et al. (2019) ‘A framework and case study for integrating household decision-making into postearthquake recovery models’, International Journal of Disaster Risk Reduction, 37, p. 101167.

Caribbean Disaster Emergency Management Agency (2021) Haiti Earthquake: Final Situation Report #12. St. Michael, Barbados. Available at: https://www.cdema.org/images/2021/09/FINAL_CDEMA_Situation_Report_12_Haiti_Earthquake_14Sep2021.pdf (Accessed: 27 April 2023).

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

Costa, R., Haukaas, T. and Chang, S.E. (2022) ‘Predicting population displacements after earthquakes’, Sustainable and Resilient Infrastructure, 7(4), pp. 253–271. Available at: https://doi.org/10.1080/23789689.2020.1746047.

Costa, R., Wang, C. and Baker, J.W. (2022) ‘Integrating Place Attachment into Housing Recovery Simulations to Estimate Population Losses’, Natural Hazards Review, 23(4), p. 04022021. Available at: https://doi.org/10.1061/(ASCE)NH.1527-6996.0000571.

Engler, D.T. et al. (2022) ‘Partitioning Ground Motion Uncertainty When Conditioned on Station Data’, Bulletin of the Seismological Society of America, 112(2), pp. 1060–1079. Available at: https://doi.org/10.1785/0120210177.

Esnard, A.-M. and Sapat, A. (2014) Displaced by Disaster: Recovery and Resilience in a Globalizing World. New York: Routledge. Available at: https://doi.org/10.4324/9780203728291. FlowMinder (2021) Haiti: Earthquake on 14 August 2021 (Version 1.2). Available at: https://www.flowminder.org/media/dpxfefl4/haitiearthquake_report_27-aug_report-2_eng_v12_final.pdf (Accessed: 27 April 2023).

Greer, A. (2015) Household residential decision-making in the wake of disaster: cases from Hurricane Sandy. University of Delaware. Available at: https://udspace.udel.edu/handle/19716/31364 (Accessed: 25 November 2022).

Grinberger, A.Y. and Felsenstein, D. (2016) ‘Dynamic agent based simulation of welfare effects of urban disasters’, Computers, Environment and Urban Systems, 59, pp. 129–141. Available at: https://doi.org/10.1016/j.compenvurbsys.2016.06.005.

Hayes, G.P. et al. (2015) ‘Rapid characterization of the 2015 M w 7.8 Gorkha, Nepal, earthquake sequence and its seismotectonic context’, Seismological Research Letters, 86(6), pp. 1557–1567.

Heath, D.C. et al. (2020) 'A global hybrid VS 30 map with a topographic slope–based default and regional map insets', Earthquake Spectra, 36(3), pp. 1570–1584.

Henry, J. (2013) 'Return or relocate? An inductive analysis of decision-making in a disaster', Disasters, 37(2), pp. 293–316. Available at: https://doi.org/10.1111/j.1467-7717.2012.01303.x.

IDMC (2018) GRID Methodological Annex. Available at: https://www.internal-displacement.org/globalreport/grid2018/downloads/report/2018-GRID-methodological-annex.pdf (Accessed: 10 January 2023).

IDMC (2019) Disaster Displacement - A global review, 2008-2018. Available at: https://www.internaldisplacement.org/publications/disaster-displacement-a-global-review (Accessed: 29 March 2023). IDMC (2020) GRID Methodology. Available at: https://www.internal-displacement.org/globalreport/grid2020/downloads/2020-IDMC-GRID-methodology.pdf (Accessed: 10 January 2023). IDMC (no date) 'Global Internal Displacement Database'. Available at: https://www.internaldisplacement.org/database (Accessed: 27 April 2023).

International Centre for Integrated Mountain Development (2015) Lessons from Nepal's Gorkha earthquake 2015. Kathmandu, Nepal.

Japan Cabinet Office (2017) Disaster Report for 2016 Kumamoto earthquake. Available at: https://www.bousai.go.jp/updates/h280414jishin/pdf/h280414jishin_39.pdf (Accessed: 27 April 2023).

Kim, J. and Oh, S.S. (2014) 'The virtuous circle in disaster recovery: who returns and stays in town after disaster evacuation?', Journal of Risk Research, 17(5), pp. 665–682. Available at: https://doi.org/10.1080/13669877.2013.822917.

Kolbe, A.R. et al. (2010) '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), pp. 281–297. Available at: https://doi.org/10.1080/13623699.2010.535279.

Lee, Y.-J., Sugiura, H. and Gečienė, I. (2017) 'Chapter 15 - Stay or Relocate: The Roles of Networks After the Great East Japan Earthquake∗∗This chapter is a modified and extended version of Lee and Sugiura (2014) in association with Ingrida Gečienė.', in E.C. Jones and A.J. Faas (eds) Social Network Analysis of Disaster Response, Recovery, and Adaptation. Butterworth-Heinemann, pp. 223–238. Available at: https://doi.org/10.1016/B978-0-12-805196-2.00015-7.

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

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

Mayer, J. et al. (2020) 'Drivers of post-disaster relocations: The case of Moore and Hattiesburg tornados', International Journal of Disaster Risk Reduction, 49, p. 101643. Available at: https://doi.org/10.1016/j.ijdrr.2020.101643.

Mitchell, C.M., Esnard, A.-M. and Sapat, A. (2012) 'Hurricane Events, Population Displacement, and Sheltering Provision in the United States', Natural Hazards Review, 13(2), pp. 150–161. Available at: https://doi.org/10.1061/(ASCE)NH.1527-6996.0000064.

Nejat, A., Cong, Z. and Liang, D. (2016) 'Family Structures, Relationships, and Housing Recovery Decisions after Hurricane Sandy', Buildings, 6(2), p. 14. Available at: https://doi.org/10.3390/buildings6020014.

Nejat, A. and Damnjanovic, I. (2012) 'Agent-Based Modeling of Behavioral Housing Recovery Following Disasters', Computer-Aided Civil and Infrastructure Engineering, 27(10), pp. 748–763. Available at: https://doi.org/10.1111/j.1467-8667.2012.00787.x.

Quarantelli, E.L. (1982) 'General and particular observations on sheltering and housing in American disasters', Disasters, 6(4), pp. 277–281. Available at: https://doi.org/10.1111/j.14677717.1982.tb00550.x.

Silva, V. et al. (2014) 'Development of the OpenQuake engine, the Global Earthquake Model's opensource software for seismic risk assessment', Natural Hazards, 72, pp. 1409–1427.

Wilson, R. et al. (2016) 'Rapid and Near Real-Time Assessments of Population Displacement Using Mobile Phone Data Following Disasters: The 2015 Nepal Earthquake', PLoS Currents, 8, p. ecurrents.dis.d073fbece328e4c39087bc086d694b5c. Available at: https://doi.org/10.1371/currents.dis.d073fbece328e4c39087bc086d694b5c.

Yabe, T. et al. (2020) 'Understanding post-disaster population recovery patterns', Journal of The Royal Society Interface, 17(163), p. 20190532. Available at: https://doi.org/10.1098/rsif.2019.0532.

Yabe, T. et al. (2022) 'Mobile phone location data for disasters: A review from natural hazards and epidemics', Computers, Environment and Urban Systems, 94, p. 101777. Available at: https://doi.org/10.1016/j.compenvurbsys.2022.101777.

Yepes-Estrada, C. et al. (2023) 'Global Exposure Modeling for Earthquake Risk Assessment', Earthquake Spectra [In review].