Do social adaptations increase earthquake resilience?

Citation for published version:
Bhloscaidh, MN, McCloskey, J, Pelling, M & Naylor, M 2021, 'Do social adaptations increase earthquake resilience?', *International Journal of Disaster Risk Reduction*, vol. 52, 101972. https://doi.org/10.1016/j.ijdrr.2020.101972

Digital Object Identifier (DOI):
10.1016/j.ijdrr.2020.101972

Published In:
International Journal of Disaster Risk Reduction

Do social adaptations increase earthquake resilience?

Mairead Nic Bhloscaidh School of Geosciences, University of Edinburgh, Grant Institute, Kings Buildings, EH9 3FE

John McCloskey orcid.org/0000-0003-4558-7717 School of Geosciences, University of Edinburgh, Grant Institute, Kings Buildings, EH9 3FE

Mark Pelling, School of Geography, Kings College, Strand, London WC2R

Mark Naylor, School of Geosciences, University of Edinburgh, Grant Institute, Kings Buildings, EH9 3FE.

*Correspondence to: John McCloskey *orcid.org/0000-0003-4558-7717* School of Geosciences, University of Edinburgh, Grant Institute, Kings Buildings, EH9 3FE john.mccloskey@ed.ac.uk

Abstract

Grandparents in earthquake-prone Chile teach children to identify load-bearing walls, and the Philippines has developed an internationally respected disaster management system. Do such low-cost, social adaptations increase community resilience to earthquakes, or are poorer countries forever doomed to large death tolls in small earthquakes? We attempt to answer this question by quantifying the vulnerability of exposed populations to a set of earthquakes recorded in the USGS PAGER system. We first remove the effect of strong shaking by statistically modelling published mortality, shaking intensity and population exposure data; unexplained variance from this purely physical model is dominated by, and its systematics therefore illuminate, the contribution of socio-economic factors to increasing earthquake mortality. We find that this variance partitions countries in terms of basic socio-economic measures and allows the definition of an Earthquake Vulnerability Index, which identifies both anomalously resilient and anomalously vulnerable countries. Unsurprisingly, wealthy countries perform well, while in general poor countries are more vulnerable. However some low-GDP countries rival even the richest in their ability to resist shaking, suggesting that social and political will can increase resilience. Until expensive engineering solutions become more universally available, the objective targeting of resources at relatively low-cost interventions might help reverse the trend of increasing mortality in earthquakes.

1. Introduction

Earthquakes represent high-impact, low-probability hazards. Their forecasting, despite significant advances in observing, understanding and modelling the physical process, is poorly constrained by current science in both space and time. This compounds the problem of persuading governments to prioritise building earthquake resilience against their response to more focused threats, particularly in the absence of proven, effective and affordable interventions. Consequently, earthquake resilience remains low and earthquake mortality continues to grow exponentially.

Here, we describe a method to quantify earthquake vulnerability, and use it to identify countries whose resilience to earthquake shaking, despite low GDP, demonstrates the action of ill-defined, low-cost interventions which, if properly understood, might be applied internationally to increase earthquake resilience. We argue that, until engineering solutions become more universally affordable, quantifying vulnerability and thereby identifying evidence-based interventions, could slow the increase in earthquake deaths.

Globally, population vulnerability to earthquakes is strongly variable[1,2]; events with similar amounts of shaking produce vastly different outcomes. Here we generalise the idea of earthquake vulnerability to: the set of compound factors which tend to influence mortality in a population exposed to strong shaking. Vulnerability in this context applies to a population as a whole, incorporating a range of interrelated social, geographical and engineering factors. Here, we do not attempt to identify the component influences in the usual way for risk modelling, much less attempt to model them explicitly. We attempt to access the aggregated vulnerability effect by modelling earthquake mortality as a function of hazard and exposure only, and exploring to what extent this fails to explain the mortality data from large earthquakes since 1960. In this sense, we consider a kind of “Mortality Risk”, which we assume to be a separable function of 1) the generalised vulnerability and 2) the geophysical influences of hazard and exposure.

GDP undoubtedly has a first order influence on such vulnerability; affluent countries can construct resilient buildings, for example, which undoubtedly is a factor in reducing population vulnerability[3]. To focus solely on GDP and expensive engineering, however, implies that earthquake vulnerability is "hard-wired" into existing social structures and that nothing short of reorganisation of global wealth can reduce earthquake impact. Clearly this statement requires more careful examination.

In 2010 earthquakes of magnitude Mw=7.0 and 7.1 respectively shook the cities of Port au Prince, Haiti[4,5] and Christchurch, New Zealand[6]; both produced similar distributions of modelled strong shaking around their epicentres and neither induced destructive secondary hazards. Haiti suffered more than 200,000 dead, while no one was killed in New Zealand. It is tempting to conclude that the high mortality in Haiti was simply due to poverty, corruption and the lack of robust seismic building codes and enforcement resulting in poor building quality. The commonly quoted, and essentially defeatist, aphorism "earthquakes don't kill people buildings do", implies that the only way to increase resilience to earthquakes is the improvement of building stock. High national income indisputably allows the deployment of risk-proof engineering[7] which reduces vulnerability. But this obvious economic fact does not imply that low-cost social interventions, loosely defined here as non-engineered interventions available to low-income economies – including for example hazard-conscious legislation such as that which underpins the Disaster Risk Reduction and Management system in the Phillipines[8], or developing tailored earthquake preparedness education for dissemination at sub-national and local levels, for example in curricula for schools[9] – and which might be available to the world's poor[10], are ineffective in increasing earthquake resilience. This entirely separate conclusion requires separate investigation.

Earthquake fatalities, as opposed to fatalities resulting from secondary hazards such as tsunamis or landslides, are caused by complex interactions between strong shaking and the size and vulnerability of the population exposed to them. We cannot explain the difference in mortality between the Port au

Prince and Christchurch events without considering the very different exposure of their populations. If we are to better understand vulnerability, this exposure to strong shaking, which dominates mortality, must, as far as possible, be removed from the analysis. Only then might we identify anomalously resilient communities whose socio-economic structures[11] may enhance (or compromise) resilience relative to a reasonable expected outcome conditioned by population exposure to strong shaking and, ultimately, recommend economically feasible interventions.

Past analyses of the social dimensions of earthquake vulnerability have been built largely on assessment of exposure based on population distributions relative to earthquake risk[12]; more quantitative studies have been restricted to the physical and engineering dimensions of vulnerability (for example building fragility[13]). Here we develop a quantitative methodology that will access the aggregate vulnerability for populations, which will include the social components.

From a purely geophysical perspective (i.e. neglecting both social and engineering influences including building design and construction), an earthquake produces spatially-variable shaking intensities and will be more or less fatal depending on the strength of this shaking and the number of people experiencing it; dangerous earthquakes, like Haiti, produce strong shaking for large populations.

Since 2007, the Modified Mercalli Intensity (MMI), a measure of the strength of shaking, is routinely calculated for the area affected by every damaging earthquake and is published together with the number of people estimated to have experienced shaking of different strengths. Hindcasting of earthquake shaking and population densities extends this database back to 1960[14,15]. Note that, while the MMI scale is defined with reference to, and calibrated against, Mercalli intensity (defined according to damage assessments, which would originally have incorporated local vulnerability implicitly), the PAGER published MMI values are calculated from a physical shaking model which does not take any account of the earthquake's local context. MMI values are therefore akin to an objective, vulnerability-independent forecast/forward-model of damage (which then become the basis of PAGER's full context-dependent damage forecast). The values we use here have therefore no contribution from vulnerability in their calculation, though they use a version of the Mercalli intensity scale.

The National Oceans and Atmospheric Administration (NOAA) records the number of fatalities disaggregated by likely cause of death[16]. We choose this database since we wish only to consider fatalities caused by strong shaking, though it correlates well with other databases[17-21] for the study period.

2. Methods

We begin by assuming that the number of people shaken strongly by an earthquake is a first-order control on mortality, and that therefore one indicator of likely mortality is the profile of the number of people estimated to have experienced shaking of different intensities. This is routinely estimated in the PAGER catalogue for every large earthquake globally, and is referred to here as the Shaking Intensity Profile (SIP) for the earthquake. In the absence of any other influencing factors, there would exist a weighting vector, **w,** whose components, w_k, link the number of people experiencing shaking of a given intensity, k, to the number of deaths (per thousand for example) which might be expected for that intensity; when weighted by **w**, the SIP could be expected to predict the number of deaths, y, in the event due purely to the physical effects of shaking, without any socio-economic variability. The predictor for an event i, which we term the shake potency, s, takes the form:

$$s_i = \sum_{k=1}^{K} w_k d_{ik} \quad (1)$$

where d_{ik} is the number of people exposed to shaking of Mercalli intensity $k = 1,\ldots,K$ (representing some subset of MMI=I,…,X) and w_k is a weight related to the severity of the shaking at that intensity.

If this model is well specified with respect to contributions to earthquake mortality from shaking, then, in a world in which we could accurately measure shaking strength everywhere, in which we knew the precise distribution of population and in which we all lived in identical societies, s could be expected to correlate strongly with earthquake mortality. In other words, provided we have a good estimate of **w,** we would expect variance in the data associated with the shaking alone (due to, for example, errors in the estimates of the SIP) to be purely stochastic.

Of course, there is clearly also a large systematic component due to unmodelled, chiefly social, influences on mortality. Since it is not possible to separate out these components, we have chosen to take the empirical approach of optimising **w** so that the model, assuming *only* stochastic errors, gives the best explanation of the data possible. This approach should be considered not as an attempt to model the mortality data, but as an attempt to make the data conform as much as possible to our assumed physical model, thereby obtaining a lower limit on the variance attributable to social influences.

We have extracted the SIPs together with the number of deaths, y, attributed to strong shaking for each event excluding those resulting in fewer than 10 deaths (giving a total data set of 232 events) and have therefore chosen a truncated Poisson model for the stochastic variance. **w** is estimated by maximum likelihood, including contributions from the SIP for MMI≥VI. For full details of the error model and optimisation procedures see the Appendix.

3. Results and Discussion

We have plotted the calculated s for each event against y in figure 1a, along with the expected mortality, λ, calculated from the optimised model (see the Appendix), as a function of s.

Since we have no real constraints on the likely magnitude of the stochastic variance, we are unable formally to identify events that are not well explained by shaking alone. Insights into the nature of the social contribution to the variance remaining after optimisation must instead come from the identification of systematic social trends within the data. We choose the World Bank assessment of the national per capita GDP as the basic measure of the social status of countries experiencing this shaking[22]. GDP correlates strongly with other development and educational indices and its wide application in comparable studies makes this a useful proxy indicator of development status for the present high-level study.

As might be expected figure 1a exhibits significant scatter. We note that, as expected, countries with high GDP tend to plot in the bottom right quadrant, where even potent earthquakes kill few people. This clearly illustrates that the variance around this model is not purely stochastic and that its systematics are related to socio-economic structures (probably dominated by quality of construction and engineering). More surprisingly, interspersed with the hot colours of USA and Japan are a large number of blue points representing potent earthquakes in poor countries, which killed only few people. Furthermore, the plot also exhibits some national differentiation of resilience among countries of similar GDP. In figure 1b, for example, some relatively low-income countries populate distinct areas of *s-y* space; the blue circles of earthquakes in the Philippines cluster in the area expected to be populated by rich countries, with two orders of magnitude greater GDP, while many of the blue stars of Iranian earthquakes plot in the upper left quadrant, where less potent events kill great numbers of people, signifying less resilience than would be expected for its GDP. This supports the view that non-physical, non-economic and, at least in part, nationally constrained factors make populations more or less vulnerable to similar levels of shaking exposure. Closer study of the earthquakes represented by these data points might expose local or national interventions which are increasing resilience of communities to strong shaking in the absence of major national investment.

We define shake vulnerability for a given earthquake, $\delta_i = y_i/\lambda_i$, to be the ratio of the number of deaths in an event i to the expected mortality due to the shaking in that event, then compute an earthquake vulnerability index $[\mathrm{EVI}]_i = \log \delta_i$, for all countries. High (low) values of this measure indicate high (low) vulnerability. A plot of EVI against log GDP (figure 2) shows the expected broad negative trend, indicating a general income-dependence of vulnerability to strong shaking. Countries which are more vulnerable than expected according to this model plot above the best-fit line, while those which are more resilient plot below. It is not the aim of this study to explain the contrasting vulnerabilities exposed in figure 2, however some speculation as to cause might help to illustrate the potential of this analysis.

The plot certainly supports the view that the death toll in the Haiti earthquake was socially influenced - the Haiti earthquake plots above the line indicating greater than expected vulnerability even for a country with this extreme poverty - but it suggests that this influence is smaller than might commonly be supposed. The anomalous vulnerability of Iran, equivalent to that of Haiti despite an order of magnitude greater GDP, might be explained by the particular geographical challenges it faces in imposing earthquake safe construction[23,24], but still identifies it as the most anomalously vulnerable nation globally. The anomalous resilience of the Philippines, on the other hand, when compared to countries like India and Guatemala, which, superficially at least, face similar geographic and economic conditions, appears exemplary and is likely due, at least in part, to its development of an integrated disaster management system[25] despite modest national income. Other contrasting pairs include Chile and Turkey, and Peru and Guatemala. Also worthy of note is that, despite their significantly higher wealth, Italians by this analysis are as vulnerable as Chinese, and Greeks are as vulnerable as Indonesians. It is, of course, easy to speculate on explanations for these contrasts, and some of them are likely to be unalterable; we believe, however, that given the importance of their implications, they deserve more detailed investigation.

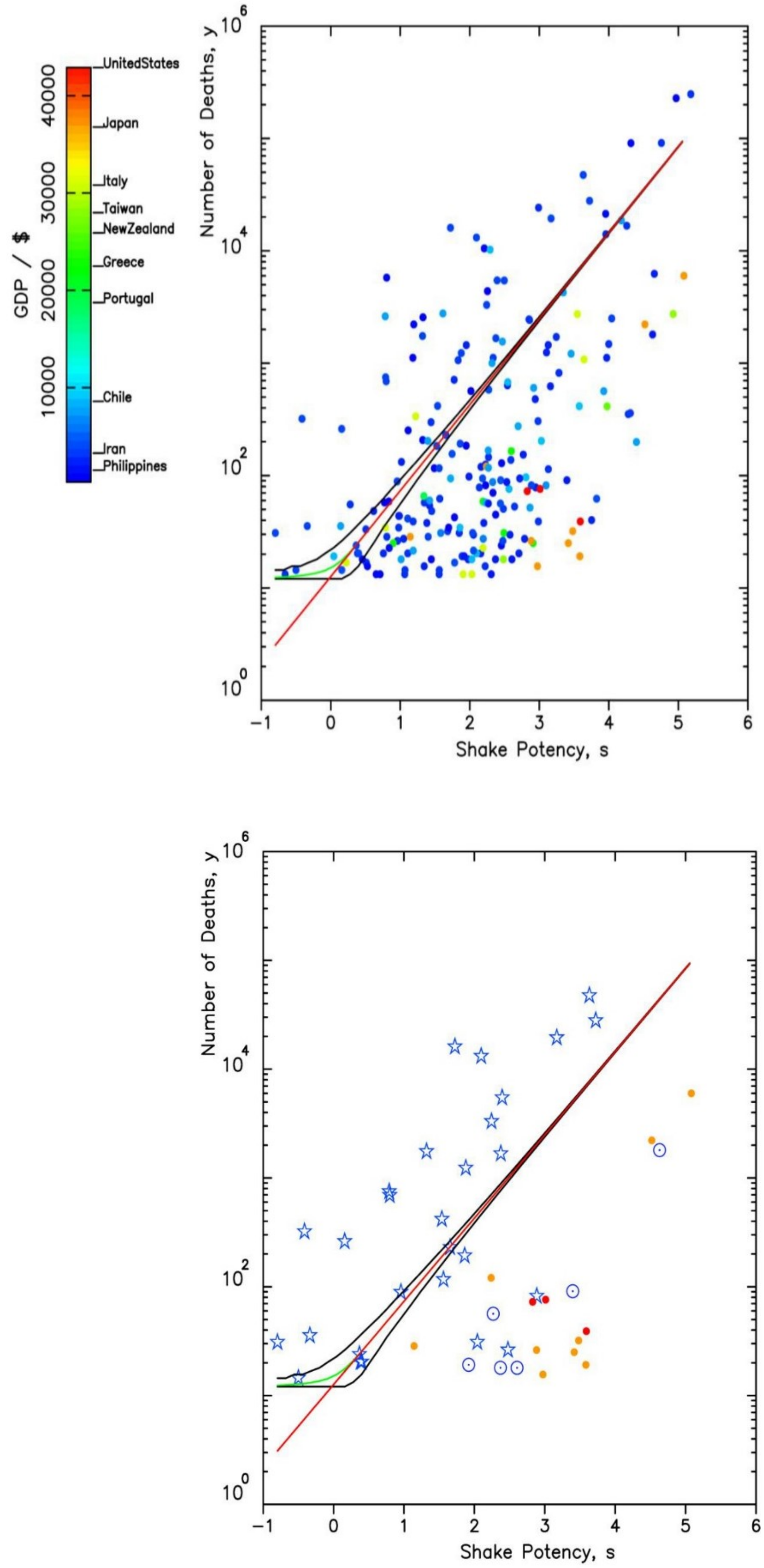
UnitedStates
Japan
Italy
Taiwan
NewZealand
Greece
Portugal
Chile
Iran
Philippines
GDP / $
10000
20000
30000
40000
Number of Deaths, y
Shake Potency, s
-1
0
1
2
3
4
5
6
Number of Deaths, y
Shake Potency, s

Figure 1

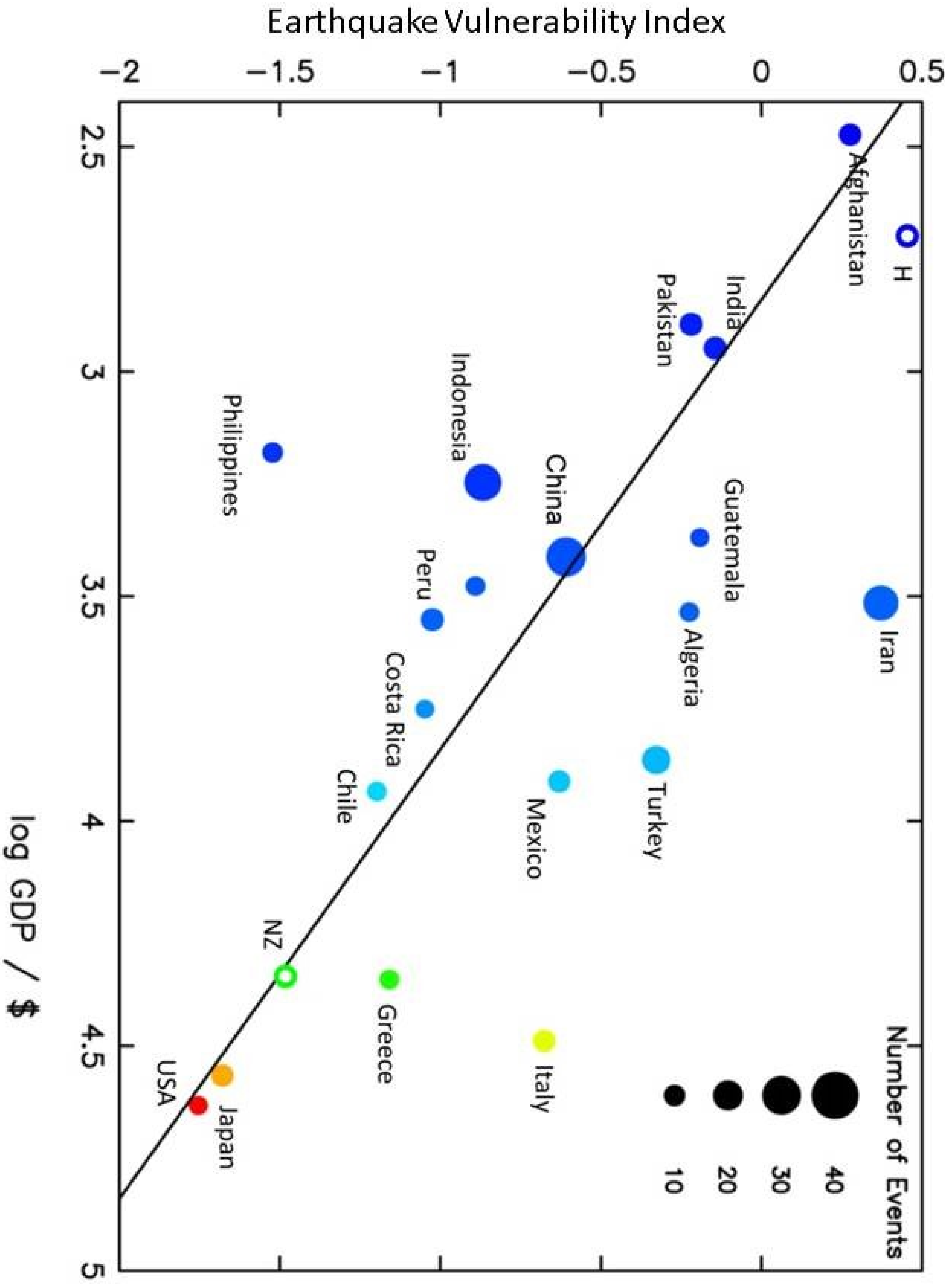
Earthquake Vulnerability Index
−2
−1.5
−1
−0.5
0
0.5
2.5
3
3.5
4
4.5
5
log GDP / $
Number of Events
10
20
30
40
H
Afghanistan
India
Pakistan
Indonesia
Philippines
China
Guatemala
Iran
Algeria
Peru
Costa Rica
Chile
Mexico
Turkey
NZ
Greece
Italy
USA
Japan

Figure 2

4. Conclusions

In conclusion, this analysis suggests that cost-neutral, social interventions have increased earthquake resilience in some countries and, conversely, that their absence exposes other populations to continuing high vulnerability. Perhaps more importantly, we believe that this type of analysis has the potential to direct sociological or political, investigations which might ultimately provide a solid basis for international cooperative learning. The sociological exploration of the origins of the contrasts revealed above, for example, might more rigorously explain their underlying causes enabling the identification and characterisation of evidence-based, low-cost interventions which in turn might provide the political impetus for action.

There can never be any substitute for better building in reducing vulnerability to strong seismic shaking, but until expensive engineering solutions become more universally available, dispassionate, rigorous quantification of vulnerability must, we believe, be placed in the vanguard of providing a scientific evidence-base to identify and disseminate affordable best-practice internationally. To date, efforts at political persuasion towards improving earthquake resilience have focused on the necessarily long-term and spatially-imprecise assessment of earthquake hazard but, in the absence of recommendations for cost-neutral interventions, earthquake mortality has continued to increase exponentially. Until we robustly quantify our assessment of earthquake resilience building, and can endorse effective and affordable responses to this poorly-defined, high-impact, low-probability threat, investment will likely remain a low priority across much of the developing world. While it does, death tolls in earthquakes will continue to grow.

Appendix

A1. **Additional Definitions**

We begin with the definition of the shake potency s in (1), and choose the form $w_k = \alpha_k 10^{k-(K+1)}$ for the weights. The mortality may be modelled using the relationship

$$\ln\lambda = a\ln s + b \quad (2)$$

where $\lambda(\mathbf{D}_i) = s_i^a(\mathbf{D}_i)e^b$ is the expected value for the number of deaths in the event, given the shaking intensity profile, $\mathbf{D}_i = [d_{i1}, \ldots, d_{iK}]$.

A2. **Choice of Error Model**

We have assumed that, provided our model is well-specified with respect to the shaking, the component of the variance associated with this process will be stochastic and can be described by a Poisson-based distribution. However the data are clearly over-dispersed with respect to a simple Poisson model, which has variance $\sigma^2(\lambda) = \lambda$ and, although the stochastic part of this may be specifically Poisson over-dispersed, i.e. $\sigma^2(\lambda) = \phi\lambda$ where ϕ is a constant, we know that a significant part of the variance is due to systematic, and not stochastic, processes, chiefly the omission from the model of social factors. Without independent constraints on the magnitude of the stochastic component, we are unable to quantify the degree to which the mortality in any event is explained, or not explained, by our model, whether the magnitude of the total variance is assumed or is a free parameter in the model.

We expect the form of the error model to control both the parameter estimates and the distribution of data that results from the optimisation. However, an alternative has been tested, which assumes a Gaussian distribution of $\ln s$, where the mean is directly proportional to the mortality in the event and the standard deviation is a free parameter, which is independent of the mortality. This model could be expected to yield very significantly different results from a Poisson based optimisation. However, we find that, although the parameter estimates and distribution of data are altered, the systematic trends in social parameters, that are the subject of this paper, remain qualitatively unchanged. In particular, the trends identified in vulnerability (shown in figure 2 for truncated Poisson), persist even using the Gaussian error model.

Our decision to use the Poisson model is in an effort to model the expected structure, if not the magnitude, of the stochastic component of the errors. For the reasons given above, we have chosen not to attempt to model the Poisson over-dispersion parameter ϕ simultaneously. The aim is that, after optimisation, as much of the data as possible is explained by the shaking process with Poisson errors, before we begin to make inferences about where and why the model fails.

A3. **The truncated Poisson distribution**

Since data for events with less than 10 deaths recorded are omitted, we use a truncated form of the Poisson distribution. The number of deaths is represented by the random variable Y; for truncation at $y = r$ the probability mass function is given by

$$
\begin{aligned}
f_r(y|\lambda) &= \Pr(y|\lambda, y > r) \\
&= \frac{\Pr(y \cap y > r|\lambda)}{\Pr(y > r|\lambda)} = \begin{cases} 0 & y \leq r \\ \dfrac{f(y|\lambda)}{1 - F(r|\lambda)} & \text{otherwise} \end{cases}
\end{aligned}
$$

where $f(y|\lambda) = \lambda^y e^{-\lambda}/y!$ is the probability mass function of the corresponding non-truncated distribution with mean λ and $F(r|\lambda) = \sum_{y=0}^{r} f(y|\lambda)$ is the cumulative mass function, evaluated at $y = r$. Defining

$$T_r(\lambda) = 1 - F(r|\lambda)$$

we can write the moment generating function as

$$M_Y(t) = \frac{1}{T_r(\lambda)}\left[e^{\lambda(e^t - 1)} - \sum_{y=0}^{r} f(y|\lambda)\, e^{ty}\right]$$

allowing us to find the expected value, $E[Y] = \mu_r(\lambda)$, and variance, ${\sigma_r}^2(\lambda)$, used to calculate the expected value and intervals in Figure 1a for the optimised model (2). We find $T_9(\lambda) \rightarrow 1$, $\mu_9(\lambda) \rightarrow \lambda$ and ${\sigma_9}^2(\lambda) \rightarrow \lambda$ at $\lambda >\approx 20$ and estimate that for $\sim 6\%$ of the data with $y \geq 10$ the simple Poisson approximation is not valid.

A4. **Maximum Likelihood Estimation**

a and *b* are unconstrained, so the set of parameters for estimation is $\theta = \{a, b, \alpha_1, \ldots, \alpha_K\}$. Since $\lambda_i = \lambda(\theta, \mathbf{D}_i)$ we write the log-likelihood function as

$$\ell(\theta|\mathbf{Y}, \mathbf{D}) = \sum_{\mathrm{i}=1}^{\mathrm{N}} \ln f_r(y_i|\theta, \mathbf{D}_i)$$

where $\mathbf{Y} = [y_1, \ldots, y_N]$ is the set of data for the number of deaths in each earthquake i and

$$\ln f_r(y_i|\theta, \mathbf{D}_i) = y_i \ln \lambda_i - \lambda_i - \ln y_i! - \ln T_r(\lambda_i)$$

Maximising the likelihood therefore involves minimising the function

$$g(\theta) = \sum_{i=1}^{N} [\lambda_i + lnT_r(\lambda_i) - y_i ln\lambda_i] \tag{3}$$

We use the gradient based BFGS optimisation algorithm[26]. So that all α_k remains positive, we set $\alpha_k = 10^{\beta_k}$ and optimise with respect to β_k. We also require $2 + K$ 1st order partial derivatives of $g(\theta)$.

A5. **Non-uniqueness of the solutions**

In this formulation, solutions for $\{\hat{b}, \hat{\beta}\}$ are not unique. Taking $\alpha' = A\hat{\alpha}$ and $s(\alpha') = As(\hat{\alpha})$ so that we have uniform scaling of both **w** and s, we can see from (2) that $\lambda(\alpha') = \lambda(\hat{\alpha})$ if $b' = b - alnA$. From (3), therefore, $g(\hat{a}, b', \alpha') = g(\hat{a}, \hat{b}, \hat{\alpha}) \equiv \gamma$. Any uniform scaling of the optimised weights corresponds to another solution for the minimum, provided the value of *b* in (2) is adjusted accordingly.

We define a set of arbitrary reference values for the optimised weights, corresponding to α^*, which represent the relative values of the components of $\hat{\alpha}$. Defining A so that, for example, $\alpha_v^* = 1$ where v is to be chosen from $k = 1, \ldots, K$, we have

$$A = \hat{\alpha}_v = 10^{\hat{\beta}_v}$$

and

$$b^*_{(\nu)} = \hat{a}\ln 10\,\hat{\beta}_\nu + \hat{b}$$

As a method for determining the value of b^*, we therefore systematically vary b, optimising all components of β. In this case, the relationship between $\hat{\beta}_\nu$ and $\hat{b}_{(\nu)}$ will be linear for all $\nu = k$, with gradient $c_\nu = c = 1/a\,ln10$ and intercept $d_\nu = b^*_{(\nu)}/a\,ln10$. This approach is preferable to, for example, setting $\beta_\nu = 0$ to find $b^*_{(\nu)}$ directly, as it provides a test that the components of β^* are robust with respect to changes in b.

A6. **Optimisation Procedure**

Based on the discussion above, the following procedure has been adopted:

1. Perform a coarse grid-search over $\{a, b\}$ at $\beta = 0$ to provide initial estimates. This is maximum likelihood line-fit to the data with $\beta = 0$.
2. Optimise β using the BFGS algorithm, with $\{a, b\}$ set according to the results of the grid-search, and the approximation to the inverse Hessian for β, $\mathbf{B}_{i=1}$, initialised to the identity matrix ($i = 1$ here refers to the 1st iteration).
3. Initialise $\mathbf{A}_{i=1}$, the approximation to the inverse Hessian for $\{a, b\}$, to the identity matrix.
4. Iterate:
    a. Optimise $\{a, b\}$with β fixed
    b. Optimise β with $\{a, b\}$ fixed,

    initialising $\mathbf{A}_i$ and $\mathbf{B}_i$, at iteration $i \geq 2$, to their *optimised* values at the previous iteration, $i - 1$. The solution converges on an arbitrary $\hat{\theta} = \theta^1 = \{\hat{a}, b^1, \beta^1\}$, depending on the start values of the parameters and the relative size of the gradients. In general, without scaling the parameters, the solution is dominated by the start value of b, since $\partial g\,(\theta)/\partial\,\beta_l 10^{l-(K+1)}$.
5. Fix $\hat{a}$ according to the results of Step 3. Vary b systematically and re-optimise β for each b.

6. Perform a line fit for $\hat{\beta}_\nu$ vs b for all $\nu = k$. Calculate b^* and $\theta^* = \{a, b^*, \alpha^* = 10^{\beta^1 - \beta_\nu^1}\}$, where β_ν^1 is the ν^{th} element of β^1 and ν has been chosen according to the standard errors in the line fits.

References

1 England, P. and Jackson, J. (2011) Uncharted seismic risk. *Nature Geoscience*, **4**, 348–349 doi:10.1038/ngeo1168

2 McCloskey, J. (2011) Focus on known active faults. *Nature Geoscience*, **4**, 494-495 doi:10.1038/ngeo1221

3 IFRC Urban governance and disaster risk reduction. In *World Disasters Report: 2010*, IFRC, Geneva, pp 139-157, (2010).

4 Calais, E. *et al*. Transpressional rupture of an unmapped fault during the 2010 Haiti earthquake *Nature Geoscience* **3**, 794–799 (2010)

5 Bilham, R. Lessons from the Haiti earthquake *Nature* **463** 878-879 (2010)

6 New Zealand earthquake report-Sep 4, 2010 at 04:35 (NZST). *GeoNet*. Earthquake Commission and GNS Science. (2010) Available at: http://www.gns.cri.nz/Home/Our-Science/Natural-Hazards/Recent-Events/Canterbury-quake/Darfield-Earthquake

7 UNU World Risk Report (2012), UNU-EHS, Bonn, accessed from http://www.ehs.unu.edu/file/get/10487.pdf

8 Philippines: Disaster Management Reference Handbook (2018) Centre for Excellence in Disaster Management and Humanitarian Assistance, https://www.cfe-dmha.org

9 Hosseini, M and Izadkhah, YO, Earthquake disaster risk management planning in schools (2006), *Disaster Prevention and Management* **15** (4), 649-661

10 Pelling, M. Review of global risk index projects: conclusions for sub-national and local approaches. In Birkmann J (ed) [second edition] Measuring Vulnerability to Natural Hazards, UNU Press, Tokyo, (2013).

11 Wisner, B., Blaikie, P., Cannon, T., Davis, I Routledge, London At Risk: Natural hazards, people's vulnerability and disasters, (2004)

12 United Nations Development Programme (UNDP) (2004) *Reducing Disaster Risk: A Challenge for Development. A Global Report*. New York: UNDP–Bureau for Crisis Prevention and Recovery (BRCP). Available at: http://www.undp.org/bcpr/disred/rdr.htm.

13 Martins, L., Silva, V. Development of a fragility and vulnerability model for global seismic risk analyses. Bull Earthquake Eng (2020). https://doi.org/10.1007/s10518-020-00885-1

14 Allen, T.I., Marano, K.D., Earle, P.S., and Wald, D.J. PAGER-CAT: A composite earthquake catalog for calibrating global fatality models. *Seism. Res. Lett.,* **80**(1), 57-62 (2009).

15 Allen, T.I., Wald, D.J., Hotovec, A.J., Lin, K., Earle, P.S. and Marano, K.D. An Atlas of ShakeMaps for selected global earthquakes.

16 USGS Open-File Report 2008-1236 (2008)

17 13 National Geophysical Data Center / World Data Service (NGDC/WDS) Significant Earthquake Database, Boulder, CO, USA. (Available at http://www.ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1). U.S. Geological Survey (USGS),. Earthquakes with 1,000 or more deaths since 1900, available at http://earthquake.usgs.gov/earthquakes/world/world_deaths.php, (2011)

18 U.S. Geological Survey (USGS), Earthquake information by year, available at http:// earthquake.usgs.gov/earthquakes/eqarchives/year/. (2011)

19 U.S. Geological Survey (USGS), Earthquakes with 50,000 or more deaths, available at http://earthquake.usgs.gov/earthquakes/world/most_destructive.php. (2011)

20 Utsu, T., 2002. A list of deadly earthquakes in the world: 1500–2000, in International Handbook of Earthquake and Engineering Seismology, Lee, W. H. K., Kanamori, H., Jennings, P. C., and Kisslinger, C. C. (editors), vol. 81A, Academic Press, Amsterdam, 691–717.

21 EM-DAT, The International Disaster Database, Centre for Research on the Epidemiology of Disasters, https://www.emdat.be

22 Worldbank GDP data available at: http://data.worldbank.org /indicator/NY.GDP.PCAP.CD

23 Jackson, J. in *Survival* (ed. Shuckburgh, E.) 123–145 (Cambridge Univ. Press, 2008).

24 Ghafory-Ashtiany, M., Hosseini, M. Post-Bam earthquake: recovery and reconstruction. *Natural Hazards* **44** 229–241, (2008).

25 Fernandez, G., Uy, H., Shaw, R. Community-Based Disaster Risk Management Experience of the Philippines. In Rajib Shaw (ed.) *Community-Based Disaster Risk Reduction*, Emerald Group Publishing Limited, pp.205-231, (2012)

26 William H. Press, Saul S. Teukolsky, William T. Vetterling, Brian P. Flannery The Art of Scientific Computing [3rd edition] Cambridge Univ. Press, (2007)

Acknowledgements

MNicB acknowledges support from the Irish Research Council for Science Engineering and Technology and the Irish Government Department of Communications, Energy and Natural resources under the Griffith Geoscience Research Awards. JMcC acknowledges support from the UK NERC under grants NE/102433X/1 and NE/M008142/1 and MN acknowledges financial support from the Royal Society of Edinburgh and Scottish Government.

Figure Legends

Fig. 1 Shake Potency plotted against the number of deaths attributed to strong shaking in fatal earthquakes. Colours of all symbols indicate the GDP. The red and green (truncated at r=10) lines show the model as in equation (2); the black lines show the structure of the Poisson uncertainties that have been used to optimise the model (according to the procedure outlined in the Appendix). A) All earthquakes with more than 10 fatalities. B) *s*-*y* space almost completely discriminates between earthquakes occurring in Iran (stars) and the Philippines (circled points). USA (red points) and Japan (orange points) are included for context.

Fig. 2. Shaking vulnerability. EVI as a function of log GDP for countries experiencing three or more earthquakes which killed more than 10 people. The best fit to the data has been estimated by using a weighted least squares method. We compare the simplest (linear) model, where we fix the gradient at -1, with a model in which the gradient is a free parameter, using the standard Akaike information criterion (which penalises overfitting). We find that the fixed gradient model is the more parsimonious fit and this is presented, though our argument is unchanged using either, since both divide the data into two roughly equal groups. Neither Haiti nor New Zealand appear in the chart since neither had three or more deadly earthquakes in the data we examined, but for illustration we show the location for the Haiti (H) earthquake and show the two deadly New Zealand (NZ) tremors as hollow symbols. This plot certainly supports the view that the difference in death toll in the Haiti and Darfield events was socially influenced, but suggests strongly that this influence is much smaller than is widely believed.