

Learning from success, not catastrophe: using counterfactual analysis to highlight successful disaster risk reduction interventions

Maricar L. Rabonza^{1, 2*}, Yolanda C. Lin³, David Lallemand^{1, 2}

¹Asian School of the Environment, College of Science, Nanyang Technological University, Singapore,

²Earth Observatory of Singapore, Singapore, ³Department of Geography and Environmental Studies,
University of New Mexico, United States

Submitted to Journal:
Frontiers in Earth Science

Specialty Section:
Geohazards and Georisks

Article type:
Original Research Article

Manuscript ID:
847196

Received on:
01 Jan 2022

Journal website link:
www.frontiersin.org

Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest

Author contribution statement

All authors contributed to the conceptualisation and design of the study. DL conceived of the idea of celebrating successes in disaster risk reduction using counterfactual analysis. MR and YL designed the analysis of the first case study. MR designed the analysis of the second case study. MR took the lead in writing the manuscript and performed analyses for the case studies. YL and DL provided critical feedback that shaped the research, analysis and manuscript.

Keywords

Counterfactual analysis, Probabilistic Risk Analysis, Disaster risk reduction (DRM) measures, School earthquake safety, Risk framework

Abstract

Word count: 224

In the aftermath of a disaster, news and research attention is focused almost entirely on catastrophic narratives and the various drivers that may have led to the disaster. Learning from failure is essential to preventing future disasters. However, hyperfixation on the catastrophe obscures potential successes at the local scale, which could serve as important examples and learning resource in effective risk mitigation. We propose the use of probabilistic downward counterfactual analysis to highlight effective risk mitigation actions that would otherwise remain unnoticed amidst a disaster. This approach uses counterfactual modelling of a past hazard event with consequences made worse (i.e. downward counterfactual) by the absence of the mitigation intervention. We further apply the probabilistic risk analysis framework to associate estimated probabilities to simulated counterfactual outcomes. We demonstrate the approach using a case study of the Nepal's School Earthquake Safety Program, implemented before the 2015 Mw 7.8 Gorkha earthquake. We calculate the probabilistic number of lives saved during the earthquake as a result of the retrofitting of schools in Kathmandu Valley since 1999. The shift in focus from realised outcome to counterfactual alternative enables the quantification of the benefits of risk reduction activities amidst disaster. Such quantified counterfactual analysis can be used to celebrate successful risk reduction interventions, providing important positive reinforcement to decision-makers with political bravery to commit to the implementation of effective measures.

Contribution to the field

While the news often highlights the catastrophe after a large hazard event, they don't focus on the buildings that remain standing, or the lives saved thanks to timely and effective disaster risk management. Instead of focusing on the realised outcomes, the use of counterfactual analysis framework, proposed here, sheds light on the effectiveness of a risk intervention by demonstrating the potential impacts without such interventions. This is the first time that counterfactual analysis is applied to estimate improvement (relative to a certain point in time) or celebrate past successes in risk mitigation - marking a fundamental shift in the application of counterfactuals in risk analysis. The framework allows the quantification of avoided losses (e.g. lives saved) by successful programs after a hazard event, as well as benefits over the lifetime of an intervention even if a hazard event that materializes the benefits hasn't occurred yet. These quantified benefits of successful risk reduction lift up the iterative, long-term, humble and politically courageous actions required for long-term resilience. This new domain of application of counterfactual analysis also has much potential across the broad spectrum of hazards as explained in the study.

Funding statement

This project is supported by the National Research Foundation, Prime Minister's Office, Singapore under the NRF-NRFF2018-06 award, the Earth Observatory of Singapore, the National Research Foundation of Singapore, and the Singapore Ministry of Education under the Research Centers of Excellence initiative. MR is supported by a PhD scholarship from the Earth Observatory of Singapore.

Ethics statements

Studies involving animal subjects

Generated Statement: No animal studies are presented in this manuscript.

Studies involving human subjects

Generated Statement: No human studies are presented in this manuscript.

Inclusion of identifiable human data

Generated Statement: No potentially identifiable human images or data is presented in this study.

Data availability statement

Generated Statement: The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

In review

Learning from success, not catastrophe: using counterfactual analysis to highlight successful disaster risk reduction interventions

Maricar L. Rabonza^{1,2*}, Yolanda C. Lin³ and David Lallemand^{1,2}

¹Asian School of the Environment, Nanyang Technological University, Singapore

²Earth Observatory of Singapore, Nanyang Technological University, Singapore

³Department of Geography and Environmental Studies, University of New Mexico, Albuquerque, NM, USA

Correspondence*:

Maricar L. Rabonza

50 Nanyang Ave, Block N2-01c-63, 639798, Singapore

MARICARL001@e.ntu.edu.sg

2 ABSTRACT

In the aftermath of a disaster, news and research attention is focused almost entirely on catastrophic narratives and the various drivers that may have led to the disaster. Learning from failure is essential to preventing future disasters. However, hyperfixation on the catastrophe obscures potential successes at the local scale, which could serve as important examples and learning resource in effective risk mitigation. We propose the use of probabilistic downward counterfactual analysis to highlight effective risk mitigation actions that would otherwise remain unnoticed amidst a disaster. This approach uses counterfactual modelling of a past hazard event with consequences made worse (i.e. downward counterfactual) by the absence of the mitigation intervention. We further apply the probabilistic risk analysis framework to associate estimated probabilities to simulated counterfactual outcomes. We demonstrate the approach using a case study of the Nepal's School Earthquake Safety Program, implemented before the 2015 M_w 7.8 Gorkha earthquake. We calculate the probabilistic number of lives saved during the earthquake as a result of the retrofitting of schools in Kathmandu Valley since 1999. The shift in focus from realised outcome to counterfactual alternative enables the quantification of the benefits of risk reduction activities amidst disaster. Such quantified counterfactual analysis can be used to celebrate successful risk reduction interventions, providing important positive reinforcement to decision-makers with political bravery to commit to the implementation of effective measures.

Keywords: counterfactual analysis, probabilistic risk, disaster risk reduction, risk framework, school earthquake safety

1 INTRODUCTION

Success in disaster risk management (DRM) means that natural hazard events do not become disasters, and communities continue to function and be resilient to shocks and stresses from hazards. Since the extent of a disaster can be characterised by loss of life, and disruptions to the physical, built and social environments, (Mileti, 1999; Smith, 2005; Moore, 1958), the extent of success of risk interventions manifest primarily as reduced impact. As such, success is measured as an *absence* (e.g. no damage, fewer casualties, etc). This

26 poses a challenge for recognising and incentivising important investments in DRM interventions since they
27 are made invisible by their very nature.

28 In the aftermath of earthquakes, storms and floods, narratives of catastrophe dominate the interest of
29 media, political and research communities. However, this hyper-fixation on the catastrophe can obscure
30 important successes amid the broader disaster. Another challenge is to recognize successful interventions
31 if the hazard they were designed for ~~have~~ not yet occurred. This happens when we rely on a disaster
32 occurrence to make mitigation benefits visible. For extreme and rare hazard events for example, the benefits
33 of risk reduction may be perceived far in the future only if the benefits manifest as reduced impact. Because
34 of the significant time delay between the interventions and their benefits being manifested, the interventions
35 could be seen as unsuccessful or squandered. These are two of the challenges described in Lallemand and
36 Rabonza et al. (Forthcoming, 2022) where successful DRM interventions are made invisible: "invisible
37 success in the midst of broader disaster", and "invisible success due to yet unrealised benefits." These
38 'invisible successes' of mitigation interventions are related to a cognitive tendency called 'outcome bias' -
39 the tendency to judge the quality of a decision by the outcome alone (Robson, 2019).

40 In this paper, we propose to address this bias through the use of probabilistic downward counterfactual
41 analysis, and highlight effective risk reduction activities in terms of probabilistic lives saved. Two
42 applications are presented to model how the consequences of a hazard event would be made worse
43 by the absence of a risk reduction intervention (i.e. downward counterfactual). The first application
44 estimates the benefits of an intervention in a past earthquake through comparison of fatalities modelled
45 without the risk intervention and actual fatalities. The second application estimates the probabilistic benefits
46 of a mitigation for a hazard that has not yet occurred. Instead of an actual past event, a hazard model is
47 used to calculate the intervention's benefits.

48 The significance and novelty of this work is in shifting our perception of the benefits of risk reduction
49 intervention, by using an appropriate counterfactual scenario as baseline against which to calculate and
50 judge these benefits. Rather than focusing entirely on *realised outcomes*, the analysis of *counterfactual
51 alternatives* shines light on the value of a mitigation intervention by demonstrating what would have been
52 without such intervention. Downward counterfactual risk analysis has only so far been used to identify
53 how much worse impacts could have been for the purpose of insurance, preparedness, or future mitigation
54 (e.g. Lin et al., 2020; Aspinall and Woo, 2019; Woo, 2019; Woo and Mignan, 2018; Shepherd et al.,
55 2018; Woo et al., 2017; Oughton et al., 2019; Aspinall and Woo, 2019). This study pioneers a systematic
56 approach to create incentives to good decision-making on the basis of probabilistic risk. The quantification
57 of probabilistic lives saved by effective risk reduction programs in a major hazard event serves as a powerful
58 indicator of the intervention's success that would otherwise remain unnoticed amidst a disaster. In addition,
59 the calculated probabilistic benefits over the lifetime of an intervention provides important incentive and
60 encouragement to decision-makers committed to implement effective measures even if the benefits are not
61 materialized yet by the occurrence of a hazard event. Altogether, this work is a new domain of application
62 of counterfactual analysis with much potential across the broad spectrum of hazards.

63 The proposed framework has significant implications to multiple potential stakeholders. For policymakers,
64 there is currently little political capital gained from investing in resilience if the benefits of such investments
65 are invisible. By having the benefits of their risk reduction investments visible to their constituents,
66 policymakers will be incentivised for risk-informed decision-making. For donors and funders, this
67 framework would enable them to monitor progress in terms of probabilistic impacts reduced, even if
68 such benefits remain unrealized until a disaster strikes. For disaster risk management practitioners, while it
69 is important to learn from failures, it is equally important to learn from successes, and share them broadly

70 so they can be emulated, scaled, and adapted in other contexts where they are needed. Importantly, it
 71 also provides a mechanism to recognise and elevate the important, humble, long-term and dedicated work
 72 conducted by many to keep our communities safe, even when their work is unseen.

73 The paper is organized as follows. Section 2 introduces the proposed framework in the context of risk
 74 analysis and probabilistic modelling. In Section 3, we describe the earthquake risk intervention that will be
 75 the focus of our two applications: the school earthquake retrofitting program in Nepal, implemented before
 76 the 2015 M_w 7.8 Gorkha earthquake, herein called Gorkha earthquake. In the subsequent sections, we
 77 present the data (Section 4), methods (Section 5) and results (Section 6) for two applications that shed light
 78 on the benefits of the retrofitting program. The first application calculates the probabilistic number of lives
 79 saved during the Gorkha earthquake as a result of the retrofitting of schools in Kathmandu valley since
 80 1997. The second application calculates future probabilistic lives saved by the retrofitting program based
 81 on a probabilistic seismic hazard model for Kathmandu Valley. This is followed by discussion (Section 7)
 82 and conclusion (Section 8).

2 COUNTERFACTUAL RISK ANALYSIS FRAMEWORK

83 Counterfactual analysis allows the exploration of alternative branches of history by creating what-if
 84 scenarios (Todorova, 2015; Lewis, 2005). To apply counterfactual analysis in disaster risk analysis, the
 85 realised event and the counterfactual are characterised in terms of their risk parameters (e.g. Lin et al., 2020;
 86 Lallement and Rabonza et al., Forthcoming, 2022). Disaster risk is typically characterised as a function of:
 87 (a) Hazard, the likelihood of potential damaging events, (b) Exposure, the characteristics of assets such as
 88 people, buildings and infrastructure and (c) Vulnerability, the susceptibility of the exposed assets to sustain
 89 impact for a given hazard intensity (UNISDR, 2009). Therefore, the realised event's impact is expressed as:

$$I_{realised} = f(\theta_H, \theta_E, \theta_V), \quad (1)$$

90 where θ_H , θ_E , and θ_V are the hazard, exposure and vulnerability parameters consecutively. Modifications
 91 (δ) of one or multiple parameters that define the realised event allows one to define the impact of a
 92 counterfactual event:

$$I_{counterfactual} = f(\theta_H + \delta_H, \theta_E + \delta_E, \theta_V + \delta_V), \quad (2)$$

93 To study a range of counterfactual events, the parameters in Equation 2 are treated as random variables
 94 with known probability distributions. The joint-probability of the parameters then defines the probability of
 95 the counterfactual. In practice, this is calculated using a simulation (e.g. Monte-Carlo simulation) since
 96 there is rarely an analytical solution. The benefits (B) of effective risk mitigation is obtained by comparing
 97 the distribution of counterfactual impacts to the realised impacts (Equation 3 and Figure 1).

$$B = I_{realised} - I_{counterfactual} \quad (3)$$

3 INVISIBLE SUCCESS OF SEISMICALLY RETROFITTING SCHOOL IN NEPAL

98 In this paper, we implement the proposed framework to highlight invisible benefits of effective earthquake
 99 risk mitigation. Specifically, we focus on one of the most significant risk interventions in the recent years
 100 that conducted improved construction practices - the seismic retrofitting of school buildings in Nepal.
 101 The program's success in the midst of the 2015 Gorkha earthquake, and its benefits due to yet unrealised
 102 benefits until the occurrence of a future large earthquake are both made invisible.

103 The safety of school buildings has always been of specific concern, reflecting a particular societal care
104 for the lives of young people. School buildings also serve important recovery functions following disaster
105 such as congregation points for the community, and sites for emergency shelters and health services (Dixit
106 et al., 2014).

107 School buildings in Nepal are recognized to be at high risk amidst the region's high seismicity from the
108 convergence of the Indian tectonic plate with the Eurasian plate, and due to informal construction practices
109 done without engineering guidance (Marasini et al., 2020). Damage to school buildings was extensive
110 from large earthquakes in recent history - the 1988 M_w 6.6 Udayapur earthquake (Gupta, 1988), and the
111 2011 M_w 6.9 Sikkim/Nepal border earthquake (Rai et al., 2012). The 2015 Gorkha earthquake is a unique
112 example in terms of damage to schools because the earthquake happened on a Saturday, whilst the school
113 was not in session. Had the earthquake hit on a school day, over one million students would have been
114 affected (Dixit et al., 2014).

115 Seismic retrofitting of school buildings started in 1997 through the leadership of the National Society
116 for Earthquake Technology (NSET) as part of the Nepal's School Earthquake Safety Program (SESP)
117 (Marasini, 2019). By the time of the Gorkha earthquake in 2015, 300 schools had been retrofitted, 160
118 of which were in the most affected districts (78 in Kathmandu). It was a big achievement that none of
119 the schools retrofitted under SESP collapsed or needed major repairs after the earthquake. Because the
120 buildings were found to be structurally sound, all the retrofitted buildings served as safe shelters and
121 required fewer temporary classrooms (Marasini, 2019).

122 Following the direction of SESP towards safe learning facilities, the Government of Nepal aims to achieve
123 minimum school safety criteria nationwide by 2030 through the Comprehensive School Safety Master
124 Plan developed by Nepal's Ministry of Education, Science and Technology (CEHRDC, 2018) based on the
125 global Comprehensive School Safety Framework (UNISDR and GADRRRES, 2017). Recognizing the
126 need to strengthen more than 60,000 school buildings all over Nepal (Marasini et al., 2020), one of the
127 activities in the Master Plan is to retrofit school buildings in earthquake-affected areas.

4 DATA

128 4.1 Exposure: Building portfolio characteristics

129 We use data of 5,011 school buildings in Kathmandu Valley that consist of 4,941 non-retrofitted buildings
130 and 70 buildings retrofitted for earthquake resilience under SESP. Shown in Figure 2 is a map of the 70
131 retrofitted schools, and in Figure 3 is a map of all 5011 school buildings in the database. The dataset was
132 produced through partnership of the Open Data for Resilience Initiative and the Government of Nepal with
133 support from Kathmandu Living Lab (OpenDRI, 2012). The 70 retrofitted schools in the dataset is part of
134 the 78 retrofitted schools surveyed by NSET in Kathmandu Valley's affected areas (Marasini, 2019). Key
135 attributes of each school building are extracted such as the coordinates, number of daytime occupants (i.e.
136 occupants in a school day), number of floors and the material used for construction. The daytime occupants
137 for the 70 retrofitted schools range from 1 to 800 with a mean of 134, whereas the daytime occupants for
138 the 5011 school buildings range from 1 to 2000 with a mean of 120.

139 4.2 Vulnerability: Building fragility

140 Fragility curves represent the probability of a certain level of damage to buildings for a given earthquake
141 intensity (IM) and building class. A fragility function for building collapse ($P(Collapse|IM)$), obtained
142 through a generalized linear model based regression, reduces to Equation 4 where Φ is the cumulative
143 distribution function of the standard normal distribution, and α and β are the maximum likelihood parameter
144 estimates for the regression model (Lallemand et al., 2015).

$$P(\text{Collapse}|IM) = \Phi(\alpha + \beta \log(IM)) \quad (4)$$

145 Non-retrofitted school buildings are assigned to building classes B-, B, K5, or C2 as defined by JICA
 146 (2002)'s survey of buildings in Kathmandu Valley before the Gorkha Earthquake (see fragility curves in
 147 Figure 4 and parameters in Table 1). Fragility curves for the retrofitted buildings are not available, so we
 148 instead adopt the fragility curve for a specially designed reinforced concrete (RC) building (Building class
 149 C3).

150 Had the 70 school buildings not been retrofitted, majority of them consist of Type B buildings, which
 151 are 1-3 storey buildings made of mud mortar or cement mortar (see distribution of non-retrofitted building
 152 classes in Figure 2). Similarly, majority of the 5,011 buildings in the dataset are Type B buildings (see
 153 Figure 3).

154 4.3 Hazard models

155 To best represent the shaking at the school buildings' sites at the time of the 2015 Gorkha earthquake,
 156 use peak ground acceleration (PGA) values produced with stochastic simulations (high frequency)
 157 for Kathmandu (Figure 2). This simulation method is well-accepted by the strong-motion community
 158 because wave propagation and source radiation tend to become more stochastic at high frequencies. This
 159 hazard model for the 2015 Gorkha earthquake was selected for this study because the location of sources
 160 of the high-frequency energy (strong-motion generation areas) is a critical factor in the relatively low
 161 damage phenomenon observed in Kathmandu Valley during the 2015 Gorkha earthquake (Gallovič, 2016;
 162 Koketsu et al., 2016), aside from effects of site conditions and rupture directivity (Dixit et al., 2015; Rajaure
 163 et al., 2017; Gallovič, 2016; Koketsu et al., 2016). In addition, most ground-motion prediction equations
 164 (GMPEs) do not account for Kathmandu Valley's low damage phenomenon (Dixit et al., 2015; Martin et al.,
 165 2015; Hough et al., 2016; Takai et al., 2016). With this hazard model, PGA values at the location of the
 166 retrofitted buildings range from 0.065 to 0.149 g, and comes in a resolution of 0.0167 degrees, or around
 167 1.85km. More details about the PGA data are summarized in Chen and Wei (2019) and its companion
 168 paper, Wei et al. (2018).

169 Another hazard model we use for this paper is the probabilistic seismic hazard analysis (PSHA) for the
 170 region where the school building dataset is located (Figure 3). We adopt Stevens et al. (2018)'s PSHA model
 171 for Kathmandu that incorporates detailed geometry of the Main Himalayan thrust, site effects, and most
 172 appropriate GMPEs informed by observed PGA and damaged patterns. The probabilistic hazard model
 173 was generated using the OpenQuake engine (Pagani et al., 2014; Silva et al., 2014). We use PGA values
 174 corresponding to a 10% probability of exceedance in 50 years from Stevens et al. (2018)'s PSHA with a
 175 resolution of 0.0083 degrees (around 0.9 km). Including site effects, the school buildings are expected to
 176 have a 10% probability of exceeding shaking of 0.506 to 0.649g in any 50 year period.

5 METHODS

177 5.1 Estimating lives saved amidst 2015 Gorkha earthquake

178 This case study imagines the scenario: What if the 2015 Gorkha earthquake happened on a school day,
 179 and the seismic retrofitting program had not been implemented? With the counterfactual risk framework,
 180 we estimate the building collapse for a realised case where the 70 school buildings were retrofitted, and a
 181 counterfactual case where these buildings are not retrofitted using the data shown in Figure 2. To explore
 182 the impact of reduced fragility from the program to the final risk results, the hazard and exposure footprint

183 remain static, i.e. we use the same hazard data and building portfolio characteristics (number of schools,
184 location, daytime occupancy) for the two scenarios.

185 The probability of exceeding a school building's collapse damage state is estimated based on the peak
186 ground acceleration (PGA) at the site, daytime occupancy, building class based on construction typology,
187 and collapse fragility curves. The **realised** scenario uses fragility data for retrofitted buildings, whereas the
188 counterfactual scenario uses fragility curves for non-retrofitted building classes. A Monte Carlo simulation
189 of Bernoulli trials then generates a distribution of number of collapsed buildings in the realised case and
190 counterfactual case. We can estimate the number of avoided building collapse by comparing the building
191 collapse between the realised and counterfactual scenario.

192 We further extend the benefit calculation beyond avoided building collapse, and quantify probabilistic
193 lives saved, using the buildings' occupancy data and a 20% fatality rate from NSET's recommendation for
194 RC and masonry building class (NSET, 2000). Estimated fatalities for the counterfactual scenario represent
195 the distribution of probabilistic lives lost had the school buildings not been retrofitted. The estimated
196 fatalities for the realised scenario is a model of probabilistic lives lost as it happened in reality. Finally,
197 we interpret the probabilistic lives saved by the intervention as the difference between the means of the
198 distributions of the simulated fatalities in the counterfactual and realised scenario. The estimated fatality
199 from the simulation of the realised event can be compared to reported post-event casualty records to validate
200 the modelled casualties. All model runs are performed using R environment and programming language (R
201 Core Team, 2020) and resulting figures are produced using the packages ggplot2 (Wickham, 2016) and
202 ggridges (Wilke, 2021) (source code available at <https://github.com/ntu-dasl-sg/frontiers2021-PLS>).

203 **5.2 Estimating lives saved throughout the program's lifetime**

204 Scaling up the retrofitting program to more than 60,000 school buildings in Nepal under the
205 Comprehensive School Safety Master Plan will significantly enhance the schools' resilience to earthquakes
206 (CEHRDC, 2018). In this analysis, we imagine the downward counterfactual: 'What if the school
207 seismic retrofitting program was never and will never be implemented to thousands of school buildings in
208 Kathmandu Valley?' Given the seismic hazard of Nepal, what are the estimated school-building collapse
209 rates and fatalities expected in the next decades? The aim of this analysis is to demonstrate how to use
210 counterfactual analysis to highlight the probabilistic benefits of the school retrofit program.

211 For this case study, we make use of a building portfolio data that consists of 5011 school buildings
212 in Kathmandu Valley - a subset of the 60,000 school buildings that is aimed to be strengthened for
213 earthquake resilience (see Figure 3). In this approach, we imagine a certain point in time in the future
214 where the Government of Nepal will finish retrofitting the 5011 school buildings in our study area. With
215 this assumption, the actual scenario for our analysis means that all school buildings in our dataset will
216 be fully retrofitted. Our counterfactual scenario represents, that at this point in time in the future, all the
217 school buildings were never retrofitted because SESP and the Comprehensive School Safety Master Plan is
218 non-existent.

219 The analysis is first-order and comes with simplifications. For the two scenarios, we make use of the
220 same exposure data and hazard model (10% probability of exceedance in 50 years). For simplicity of
221 analysis, we assume that exposure remains constant over time, meaning the number of schools and its
222 occupants do not change. The only difference between the two scenarios is the forecasted building stock
223 vulnerability at the end of the program's lifetime. For the actual scenario, all 5,011 buildings are retrofitted
224 with a C3 building class' fragility. Whereas for the counterfactual scenario, all buildings will be assigned
225 non-retrofitted building classes, namely, B-, B, K5 and C2. To clarify, the counterfactual assumes that

226 the 70 buildings already retrofitted at the time of the building survey are non-retrofitted, as if the retrofit
227 program didn't exist. Using the proposed counterfactual risk framework, we estimate the probabilistic
228 building collapse for the two scenarios mentioned. We implement the fatality calculation approach used in
229 the first case study to obtain a distribution of probabilistic fatalities.

230 The simplifications are sufficient to demonstrate how the framework can highlight the benefits of the
231 school retrofit program even if an earthquake event hasn't happened yet. A modeller with more information
232 about time-dependent exposure (e.g. growing building portfolio) and vulnerability (e.g. sequential
233 retrofitting) can opt to implement this methodology at multiple points in time to get time-dependent
234 building collapse and study long term risk (Rabonza and Lallemand, 2019).

6 RESULTS

235 6.1 Lives saved amidst 2015 Gorkha earthquake

236 Our probabilistic analysis show that in the realised scenario (all buildings retrofitted), an average of 3 out
237 of the 70 school buildings collapsed, whereas for the counterfactual case (all buildings non-retrofitted), an
238 average of 12 out of the 70 school buildings collapsed. Based on these results, 9 school buildings likely
239 avoided collapse thanks to the retrofitting intervention (Figure S1). The simulation of the realised fatalities
240 during the Gorkha earthquake shows a mean of 74 fatalities, whereas counterfactual fatalities have an
241 average of 300 (Figure 5). By comparing the fatalities from the two scenarios, we estimate that the lives of
242 approximately 226 school occupants were saved in Kathmandu by the retrofit of the 70 schools.

243 6.2 Lives saved throughout the program's lifetime

244 Our model forecasts that the collapse of 2,490 buildings are likely to be avoided if all the 5,011 buildings
245 will be retrofitted based n PGA values for 10% probability of exceedance in 50 years (Figure S2). Our
246 simulation for the 'actual' scenario where all buildings are retrofitted shows a mean of 20,207 fatalities
247 whereas the fatalities from the counterfactual simulation has a mean of 79,529. Based on the counterfactual
248 analysis, 59,322 lives will be saved by the retrofitting of the 5,011 buildings (Figure 6).

7 DISCUSSION

249 7.1 Counterfactual analysis to celebrate probabilistic lives saved

250 We demonstrated two applications of the probabilistic downward counterfactual risk analysis to (1)
251 celebrate lives saved by an intervention amidst a past event, and (2) forecast lives saved throughout the
252 intervention's lifetime with the use of a probabilistic hazard model. The two applications show that even in
253 the midst of a tragic disaster, or even if a hazard event hasn't happened yet, there are often successes in risk
254 reduction intervention to celebrate. The counterfactual analysis showed that hundreds of lives are estimated
255 to be saved because of the government-led retrofitting of 70 school buildings in the dataset. The program's
256 benefit is obscured further because the Gorkha earthquake happened on a day without school sessions. Our
257 second application also estimated that tens of thousand of fatalities are likely to be avoided once the 5,011
258 school buildings in our dataset are retrofitted.

259 Although it is known that none of the retrofitted schools collapsed based on damage assessments after
260 the Gorkha earthquake, the number of fatalities in the 70 school buildings is unknown (Marasini, 2019).
261 Assuming that the actual casualties in these buildings are lower than the mean of our fatality estimates (74),
262 it would likely be due to the fragility data underestimating the structural performance of the buildings.

263 7.2 Risk benefit metric

264 In our demonstrations, the risk benefit of DRM intervention is measured in terms of a reduction in loss of
265 life - the first target metric within the Sendai Framework For Disaster Risk Reduction (UNISDR, 2015). A

266 risk benefit metric in financial units can also be used, as with typical cost-benefit analysis. However such
267 analysis tend to highlight interventions that effectively protect high-value areas instead of high-vulnerability
268 areas, which exacerbates inequities (Markhvida et al., 2020; Lallement et al., 2020).

269 More alternative risk benefit metrics for this analysis include the number of displaced people, business
270 downtime, damage to buildings and cultural heritage, psychological distress and more. For the Nepal case
271 study for example, the benefits of the retrofitting go well beyond the reduced physical vulnerability of the
272 buildings. Retrofitted schools served as immediate community shelter, field hospitals and relief centers.
273 Classes in the retrofitted buildings were operated without fear, resulting to less demand for temporary
274 classrooms (Marasini et al., 2020). Loss-avoidance is not the only invisible benefit of disaster mitigation,
275 and benefits of DRM interventions go beyond reduction of impact. Certain intervention designs can have
276 co-benefits that are social (e.g. more leisure parks), environmental (e.g. wetland afforestation), political
277 (e.g. better governance), or economic (e.g. better agriculture production) (Tanner et al., 2015).

278 **7.3 First order approach**

279 The analyses and estimates of lives saved presented are first order and serve as proof of concept of the
280 counterfactual framework to highlight successes in DRM. Following are limitations that need to be noted
281 for future work:

- 282 • The analysis did not account for fatalities from partially collapsed buildings. To account for this, one
283 may use NSET's recommendation to use a 10% fatality rate for heavily damaged buildings (NSET,
284 2000)
- 285 • The building portfolio dataset we use in the two case studies is only a subset of all the schools within
286 the study area. The dataset used for the first case study (Section 5.1) contains only 70 out of the 78
287 retrofitted schools in Kathmandu. For the second case study (Section 5.2), we also did not include
288 school building data that has no information on the occupancy and construction material.
- 289 • For the second case study, the assumption that the goal of the Government of Nepal is to finish
290 retrofitting the 5,011 buildings in our dataset is not necessarily reflective of their exact plan of action.
291 Rather, the assumption is a choice of the authors to demonstrate the framework in a simple and
292 straightforward manner.

293 In an attempt to explore how different the casualty estimates would be for different hazard models for
294 the 2015 Gorkha earthquake, we repeated the analysis in Section 5.1 using a PGA map from the USGS
295 ShakeMap (Wald and Allen, 2007). Looking at the results in Figure S3, using ShakeMap results to 355
296 lives saved. This is only a simple exploration using a different hazard model, and not a full sensitivity
297 analysis.

298 **7.4 Extending to other domains of hazard and interventions**

299 Probabilistic downward counterfactual risk analysis has potential for application to other hazards. A
300 key step of the framework is to identify which risk component the intervention influences. Earthquake
301 risk reduction, for example, influences either the reduction of exposure or vulnerability. Measures such as
302 restricting development in high-hazard zones decrease exposure, whereas better construction standards
303 decrease the structural vulnerability of buildings and infrastructure.

304 Beyond earthquake risk reduction, the proposed framework can also be used in other domains of
305 hazard. Following are few selected examples of natural hazards and corresponding interventions that could
306 be celebrated using counterfactual analysis. Enclosed in parenthesis are the risk component/s that the
307 intervention influences.

- 308 1. **Earthquake**
- 309 • Reconstruction and seismic retrofit (Vulnerability)
- 310 • Construction inspection (Vulnerability)
- 311 • Preparedness exercises (Exposure, Vulnerability)
- 312 2. **Tropical cyclone and Tsunami**
- 313 • Early warning system and timely announcements (Exposure)
- 314 • Evacuation and provision of temporary shelters (Exposure and Vulnerability)
- 315 • Public awareness about the hazard (Exposure and Vulnerability)
- 316 3. **Flood**
- 317 • Limiting urban development in flood-prone zones (Exposure, Vulnerability)
- 318 • Enhanced flood management infrastructure (Exposure, Hazard)
- 319 • Timely emergency response (Vulnerability, Exposure)
- 320 4. **Landslides**
- 321 • Early warning system via geodynamic monitoring (Exposure)
- 322 • Mitigation infrastructure, e.g. drainage systems (Exposure, Hazard)
- 323 5. **Wildfires**
- 324 • Early warning system via dynamic weather forecasts (Exposure)

8 CONCLUSION

325 In a field focused on long-term resilience to rare (i.e. volatile) hazard events, perceptions are biased by
326 realised outcomes. Perceiving no impacts when DRM work is so successful can result to policy makers
327 and society at large to undervalue the importance of proactive intervention. Shedding light on successes
328 and ‘what might have been’ not only recognizes the outstanding work of those in the industry but is also
329 a crucial component of encouraging decision-makers to continue investment in measures that keep our
330 communities and world safe.

331 We highlight the need to celebrate the often invisible successes of disaster risk reduction interventions,
332 in order to incentivise, better learn and replicate investments in such interventions. We further propose
333 and demonstrate the use of counterfactual analysis risk framework to identify, quantify and highlight these
334 invisible successes. The framework demonstrates that judgement of a risk reduction intervention should be
335 based on a broad exploration of possible outcomes, not only on specific outcomes.

CONFLICT OF INTEREST STATEMENT

336 The authors declare that the research was conducted in the absence of any commercial or financial
337 relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

338 All authors contributed to the conceptualisation and design of the study. DL conceived of the idea of
339 celebrating successes in disaster risk reduction using counterfactual analysis. MR and YL designed the
340 analysis of the first case study. MR designed the analysis of the second case study. MR took the lead in
341 writing the manuscript and performed analyses for the case studies. YL and DL provided critical feedback
342 that shaped the research, analysis and manuscript.

FUNDING

343 This project is supported by the National Research Foundation, Prime Minister's Office, Singapore under
344 the NRF-NRFF2018-06 award, the Earth Observatory of Singapore, the National Research Foundation of
345 Singapore, and the Singapore Ministry of Education under the Research Centers of Excellence initiative.
346 MR is supported by a PhD scholarship from the Earth Observatory of Singapore.

ACKNOWLEDGMENTS

347 We thank Dr. Nama Budhathoki, Kathmandu Living Labs and the GFDRR Open Data for Resilience
348 Initiative for data on school buildings in Nepal. We also thank Dr. Shengji Wei and Dr. Meng Chen for data
349 and information on the stochastic ground simulations in Kathmandu for the 2015 Gorkha earthquake.

SUPPLEMENTAL DATA

DATA AVAILABILITY STATEMENT

350 The original contributions presented in the study are included in the article. Further inquiries can be directed
351 to the corresponding author/s.

REFERENCES

- 352 Aspinall, W. and Woo, G. (2019). Counterfactual analysis of runaway volcanic explosions. *Frontiers in*
353 *Earth Science* 7, 222
- 354 CEHRDC (2018). Comprehensive School Safety Minimum Package: Volume 1 – Report. Sano Thimi,
355 Bhaktapur, Nepal: Centre For Education and Human Resource Development Accessed 2021-12-20.
356 <https://www.preventionweb.net/publication/nepal-comprehensive-school-safety-minimum-package>
- 357 Chen, M. and Wei, S. (2019). The 2015 Gorkha, Nepal, earthquake sequence: II. broadband simulation of
358 ground motion in Kathmandu. *Bulletin of the Seismological Society of America* 109, 672–687
- 359 Dixit, A. M., Ringler, A. T., Sumy, D. F., Cochran, E. S., Hough, S. E., Martin, S. S., et al. (2015).
360 Strong-motion observations of the M 7.8 Gorkha, Nepal, earthquake sequence and development of the
361 N-SHAKE strong-motion network. *Seismological Research Letters* 86, 1533–1539
- 362 Dixit, A. M., Yatabe, R., Dahal, R. K., and Bhandary, N. P. (2014). Public school earthquake safety
363 program in Nepal. *Geomatics, Natural Hazards and Risk* 5, 293–319
- 364 Gallovič, F. (2016). Modeling velocity recordings of the M w 6.0 South Napa, California, earthquake:
365 Unilateral event with weak high-frequency directivity. *Seismological Research Letters* 87, 2–14
- 366 Gupta, S. P. (1988). *Report on eastern Nepal earthquake 21 August 1988: Damages and recommendations*
367 *for repairs and reconstruction* (Asian Disaster Preparedness Center, Asian Institute of Technology)
- 368 Hough, S. E., Martin, S. S., Gahalaut, V., Joshi, A., Landes, M., and Bossu, R. (2016). A comparison of
369 observed and predicted ground motions from the 2015 Mw 7.8 Gorkha, Nepal, earthquake. *Natural*
370 *Hazards* 84, 1661–1684
- 371 JICA, M. (2002). The study on earthquake disaster mitigation in the Kathmandu Valley, Kingdom of Nepal.
372 *Japan International Cooperation Agency (JICA) and Ministry of Home Affairs (MOHA), Tokyo*, 79–80
373 <http://flagship2.nrcc.org.np/study-earthquake-disaster-mitigation-kathmandu-valley>
- 374 Koketsu, K., Miyake, H., Guo, Y., Kobayashi, H., Masuda, T., Davuluri, S., et al. (2016). Widespread
375 ground motion distribution caused by rupture directivity during the 2015 Gorkha, Nepal earthquake.
376 *Scientific reports* 6, 1–9
- 377 Lallemand, D., Kiremidjian, A., and Burton, H. (2015). Statistical procedures for developing earthquake
378 damage fragility curves. *Earthquake Engineering & Structural Dynamics* 44, 1373–1389. doi:10.1002/
379 eqe.2522

- 380 Lallement, D., Loos, S., McCaughey, J. W., Budhathoki, N., and Khan, F. (2020). *Informatics for*
381 *Equitable Recovery: Supporting equitable disaster recovery through mapping and integration of social*
382 *vulnerability into post-disaster impact assessments*. Tech. rep. doi:10.32656/IER_Final_Report_2020
- 383 Lallement and Rabonza, Lin, Y., Tadepalli, S., Wagenaar, D., Michele, N., Choong, J., et al. (Forthcoming,
384 2022). Shedding light on avoided disasters: Measuring the invisible benefits of disaster risk management
385 using probabilistic counterfactual analysis. *Global Assessment Report on Disaster Risk Reduction 2022*
386 <https://hdl.handle.net/10356/153502>
- 387 Lewis, D. (2005). On the Plurality of Worlds. *Central Works of Philosophy, Volume 5: The Twentieth*
388 *Century: Quine and After* 5, 246
- 389 Lin, Y. C., Jenkins, S. F., Chow, J. R., Biass, S., Woo, G., and Lallement, D. (2020). Modeling downward
390 counterfactual events: Unrealized disasters and why they matter. *Frontiers in Earth Science* , 443
- 391 Marasini, N. (2019). NSET Experiences on Safer Schools Initiative. In *Asian Conference on Disaster*
392 *Reduction, Ankara, Republic of Turkey* (ACM). Accessed 20 Nov 2021. <https://bit.ly/32P4pjC>
- 393 Marasini, N., Shrestha, S., Guragain, R., Shrestha, H., Prajapati, R., and Khatiwada, P. (2020). Enhancing
394 earthquake safety of schools: Lessons learned from Nepal. In *Proceedings of the 17th World Conference*
395 *on Earthquake Engineering* (Sendai, Japan), Article No. 3g–0023
- 396 Markhvida, M., Walsh, B., Hallegatte, S., and Baker, J. (2020). Quantification of disaster impacts through
397 household well-being losses. *Nature Sustainability* 3, 538–547. doi:10.1038/s41893-020-0508-7.
398 Number: 7 Publisher: Nature Publishing Group
- 399 Martin, S. S., Hough, S. E., and Hung, C. (2015). Ground motions from the 2015 Mw 7.8 Gorkha, Nepal,
400 earthquake constrained by a detailed assessment of macroseismic data. *Seismological Research Letters*
401 86, 1524–1532
- 402 Mileti, D. (1999). *Disasters by design: A reassessment of natural hazards in the United States* (Joseph
403 Henry Press)
- 404 Moore, H. E. (1958). Tornadoes over Texas: A study of Waco and San Angelo in disaster.
- 405 NSET (2000). *Seismic vulnerability of the public-school buildings of Kathmandu Valley and methods for*
406 *reducing it*. Tech. rep. <https://nset.org.np/nset2012/images/publicationfile/20130724114208.pdf>
- 407 OpenDRI (2012). *Understanding Nepal's Risks" Open Data for Resilience Initiative Project*. Tech. rep.,
408 Open Data for Resilience Initiative Project. <https://opendri.org/project/nepal/>
- 409 Oughton, E. J., Ralph, D., Pant, R., Leverett, E., Copic, J., Thacker, S., et al. (2019). Stochastic
410 counterfactual risk analysis for the vulnerability assessment of cyber-physical attacks on electricity
411 distribution infrastructure networks. *Risk Analysis* 39, 2012–2031
- 412 Pagani, M., Monelli, D., Weatherill, G., Danciu, L., Crowley, H., Silva, V., et al. (2014). Openquake
413 engine: An open hazard (and risk) software for the global earthquake model. *Seismological Research*
414 *Letters* 85, 692–702
- 415 R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for
416 Statistical Computing, Vienna, Austria
- 417 Rabonza, M. L. and Lallement, D. (2019). Accounting for time and state-dependent vulnerability of
418 structural systems doi:10.22725/ICASP13.465
- 419 Rai, D. C., Mondal, G., Singhal, V., Parool, N., Pradhan, T., and Mitra, K. (2012). Reconnaissance report
420 of the m6. 9 sikkim (india–nepal border) earthquake of 18 september 2011. *Geomatics, Natural Hazards*
421 *and Risk* 3, 99–111
- 422 Rajaure, S., Asimaki, D., Thompson, E. M., Hough, S., Martin, S., Ampuero, J., et al. (2017).
423 Characterizing the Kathmandu Valley sediment response through strong motion recordings of the
424 2015 Gorkha earthquake sequence. *Tectonophysics* 714, 146–157

- 425 Robson, D. (2019). The bias that can cause catastrophe. *BBC*
- 426 Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., et al. (2018).
427 Storylines: an alternative approach to representing uncertainty in physical aspects of climate change.
428 *Climatic change* 151, 555–571
- 429 Silva, V., Crowley, H., Pagani, M., Monelli, D., and Pinho, R. (2014). Development of the OpenQuake
430 engine, the Global Earthquake Model's open-source software for seismic risk assessment. *Natural
431 Hazards* 72, 1409–1427
- 432 Smith, D. (2005). *Through a glass darkly-a response to Stallings'" Disaster, Crisis, Collective Stress, and
433 Mass Deprivation"*, vol. 2 (Xlibris Press)
- 434 Stevens, V., Shrestha, S., and Maharjan, D. (2018). Probabilistic seismic hazard assessment of Nepal.
435 *Bulletin of the Seismological Society of America* 108, 3488–3510
- 436 Takai, N., Shigefuji, M., Rajaure, S., Bijukchhen, S., Ichiyangagi, M., Dhital, M. R., et al. (2016). Strong
437 ground motion in the Kathmandu Valley during the 2015 Gorkha, Nepal, earthquake. *Earth, Planets and
438 Space* 68, 1–8
- 439 Tanner, T., Surminski, S., Wilkinson, E., and Reid, R. (2015). *The Triple Dividend of Resilience: Realising
440 development goals through the multiple benefits of disaster risk management*. Tech. rep., Global Facility
441 for Disaster Risk Reduction and Recovery (GFDRR) at the World Bank and Overseas Development
442 Institute (ODI)
- 443 Todorova, M. (2015). Counterfactual construction of the future: Building a new methodology for forecasting.
444 *World Futures Review* 7, 30–38. doi:10.1177/1946756715587004
- 445 UNISDR (2009). *United Nations Office for Disaster Risk Reduction, UNISDR Terminology and Disaster
446 Risk Reduction*. Tech. rep., United Nations International Strategy for Disaster Reduction, Geneva,
447 Switzerland
- 448 UNISDR (2015). Sendai framework for disaster risk reduction 2015-2030. In *Third United Nations World
449 Conference on Disaster Risk Reduction (WCDRR)—Resilient People. Resilient Planet*.
- 450 UNISDR and GADRRRES (2017). Comprehensive school safety. united nations international strategy
451 for disaster reduction and global alliance for disaster risk reduction resilience in the education sector
452 Accessed 2021-12-20. <http://gadrrres.net/uploads/files/resources/CSS-Framework-2017.pdf>
- 453 Wald, D. J. and Allen, T. I. (2007). Topographic slope as a proxy for seismic site conditions and
454 amplification. *Bulletin of the Seismological Society of America* 97, 1379–1395
- 455 Wei, S., Chen, M., Wang, X., Graves, R., Lindsey, E., Wang, T., et al. (2018). The 2015 Gorkha (Nepal)
456 earthquake sequence: I. Source modeling and deterministic 3D ground shaking. *Tectonophysics* 722,
457 447–461
- 458 Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis* (Springer-Verlag New York)
- 459 Wilke, C. O. (2021). *ggridges: Ridgeline Plots in 'ggplot2'*. R package version 0.5.3
- 460 Woo, G. (2019). Downward counterfactual search for extreme events. *Frontiers in Earth Science* 7, 340
- 461 Woo, G., Maynard, T., and Seria, J. (2017). Reimagining history: counterfactual risk analysis. *Lloyd's
462 emerging risk report, London*
- 463 Woo, G. and Mignan, A. (2018). Counterfactual analysis of runaway earthquakes. *Seismological Research
464 Letters* 89, 2266–2273

FIGURE CAPTIONS

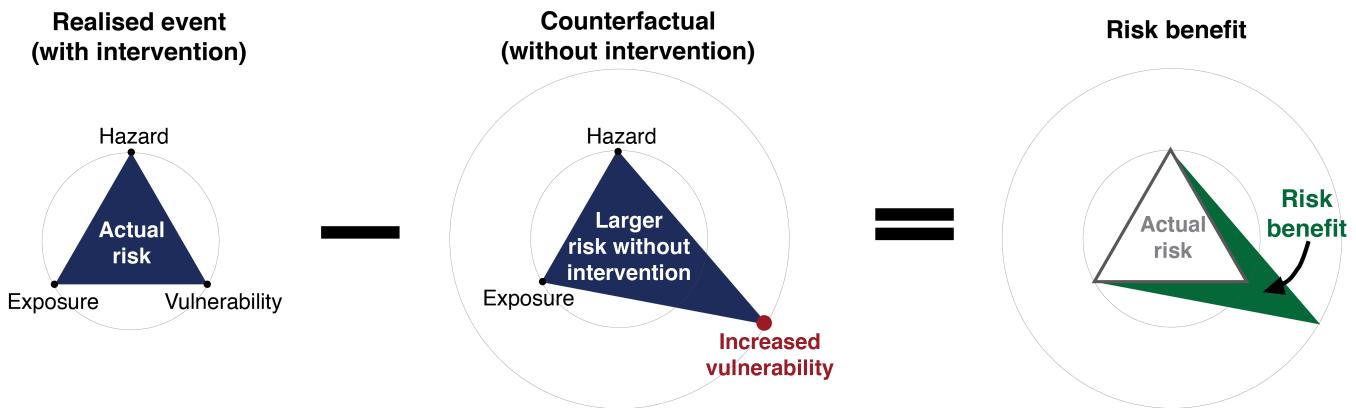


Figure 1. The concept of the counterfactual risk analysis framework for quantifying the probabilistic benefits of effective risk reduction

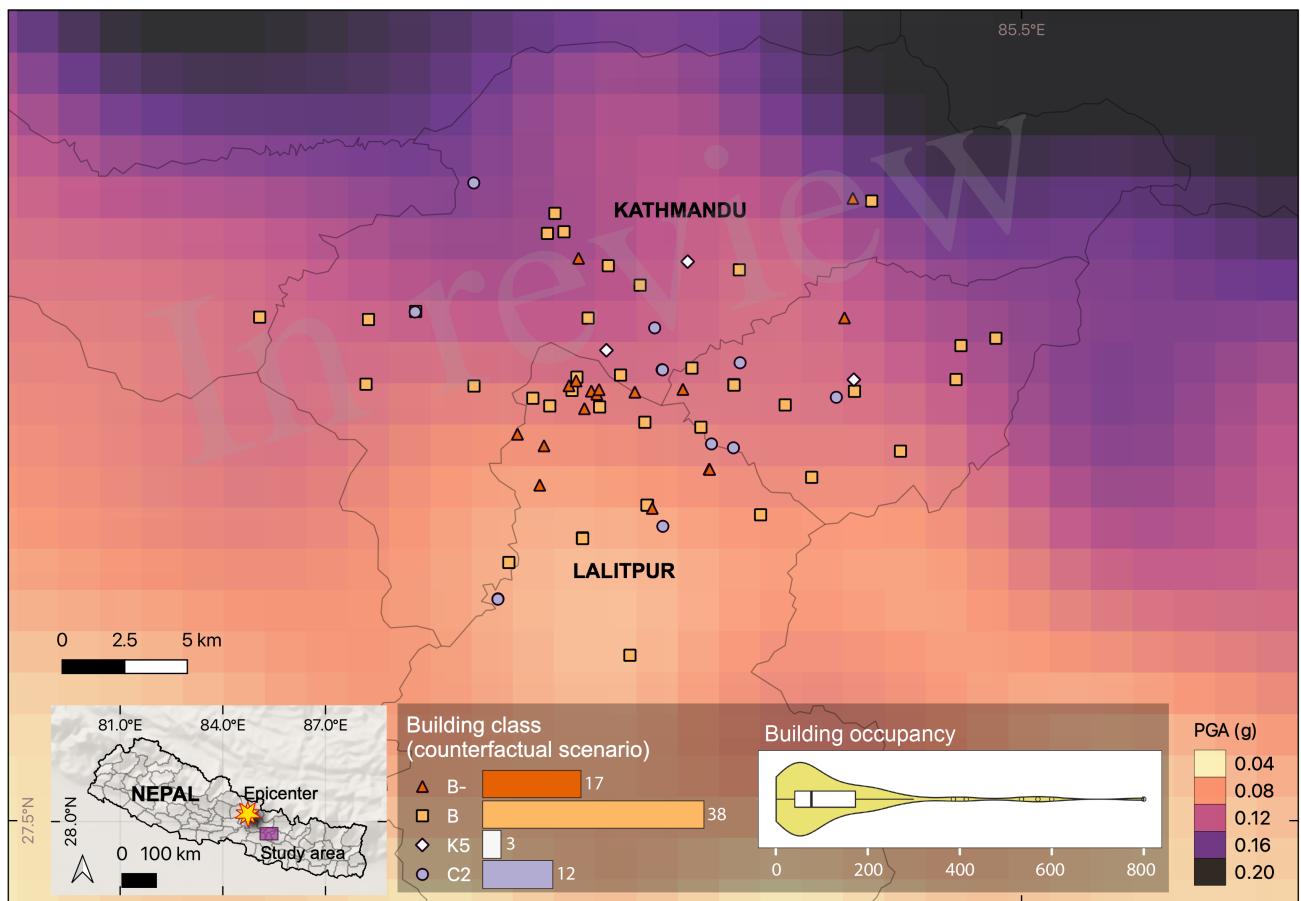


Figure 2. Datasets used for the case study in Section 5.1 to estimate the lives saved by the retrofitting of 70 schools amidst the 2015 Gorkha earthquake. For the realised scenario, all the 70 retrofitted school buildings shown on the map are assigned as building class C3. For the counterfactual scenario, all buildings were assumed to be non-retrofitted and assigned to building classes shown in the bar graph at the bottom. The buildings' daytime occupants range from 1 to 800 with distribution as a violin plot at the bottom. The basemap shows the peak ground acceleration (in g-units) adopted from Chen and Wei (2019).

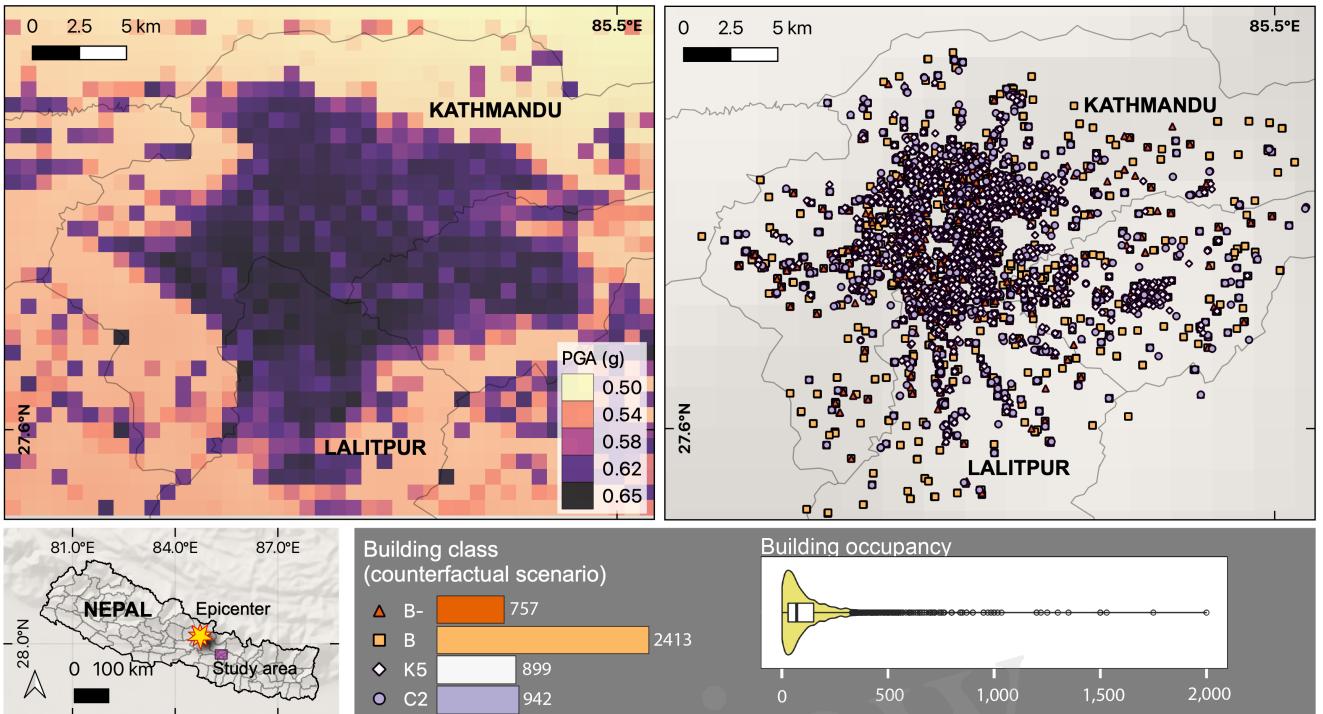


Figure 3. Datasets used for the case study in Section 5.2 to forecast the lives saved by the retrofitting of the 5,011 school buildings in the event of a 10% in 50 years shaking. Shown in the top left is a map of PGA in g-units generated by Stevens et al. (2018) for 10% exceedance in 50 year shaking. The location of the 5,011 retrofitted school buildings are shown in the top right. For the realised scenario, all buildings were retrofitted and categorized as building class C3. For the counterfactual scenario, all buildings were assumed to be non-retrofitted and assigned to building classes shown in the bar graph at the bottom. The buildings' daytime occupants range from 1 to 2000 with distribution as a violin plot at the bottom.

Table 1. Building classes for schools in Nepal and associated fragility curve parameters. (Data source: (OpenDRI, 2012; JICA, 2002)

Building type	Description	Structural state of building	Fragility curve parameters	
			α	β
B-	B-type rural buildings with traditional materials and height up to three storeys, or with cement mortar in brick masonry and height up to five storeys.	Un-retrofitted	1.129	0.790
B	Buildings with mud mortar, ordinary brick, large blocks, natural dressed stone with height up to 1 storey, or with cement mortar in brick masonry and height up to 3 storeys.	Un-retrofitted	1.066	0.858
K5	Mason-designed 5 storey RC buildings	Un-retrofitted	1.118	1.246
C2	Reinforced buildings (RC) designed for normal load only, or mason designed 3 storey RC buildings.	Un-retrofitted	-0.137	0.772
C3	Specially designed RC buildings	Retrofitted	-0.758	0.445

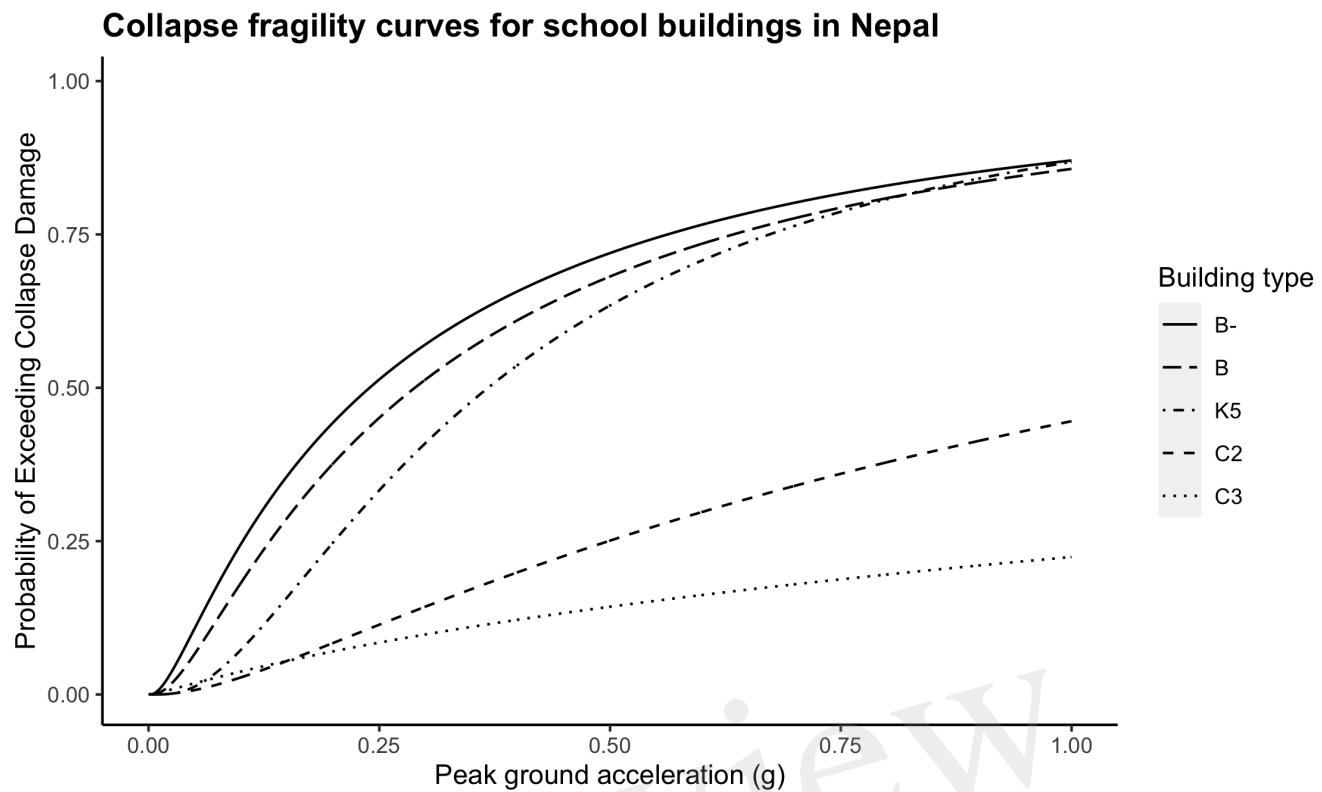


Figure 4. Collapse fragility curves for the building classes in the full building portfolio adopted from (JICA, 2002). Non-retrofitted building classes include B-, B, K5, and C2, while the retrofitted buildings are assigned as type C3. Refer to Table 1 for complete descriptions of building classes.

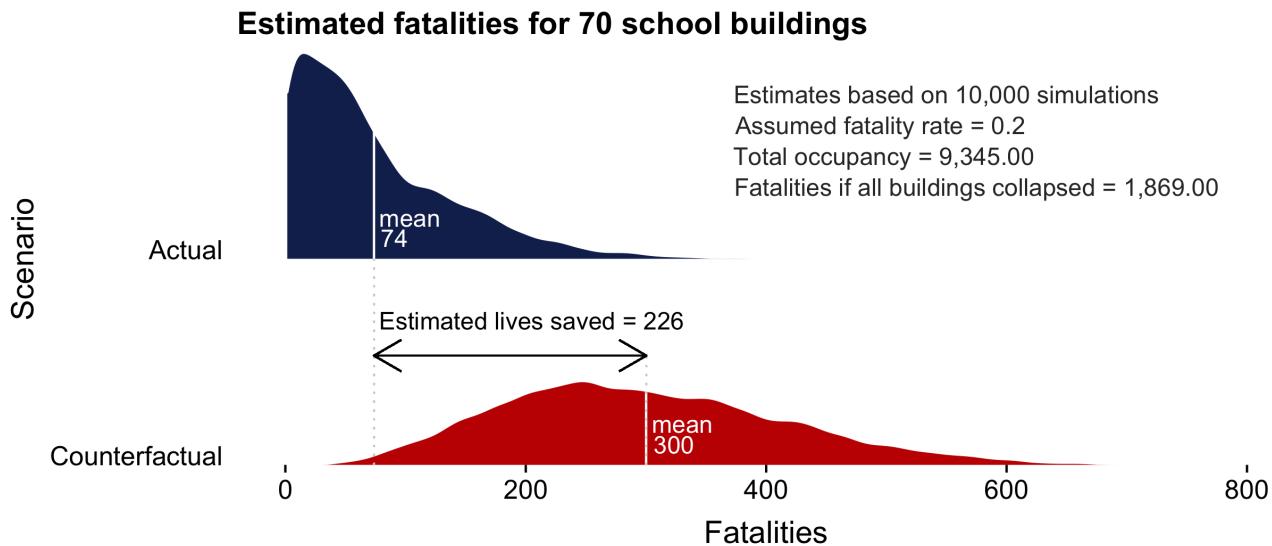


Figure 5. Distribution of estimated fatalities from the 2015 M_w 7.8 Gorkha earthquake based on earthquake intensity values from Chen and Wei (2019). Two scenarios are shown: the actual scenario where all 70 school buildings were retrofitted prior to the 2015 Gorkha earthquake, and a counterfactual scenario where the schools were not retrofitted. The difference between the means of the actual and counterfactual scenario represent the estimated lives saved by the retrofit program. In reality, none of the 70 school buildings collapsed after the Gorkha earthquake. Our probabilistic analysis show an estimated 226 lives saved by the schools retrofit program during the Gorkha earthquake.

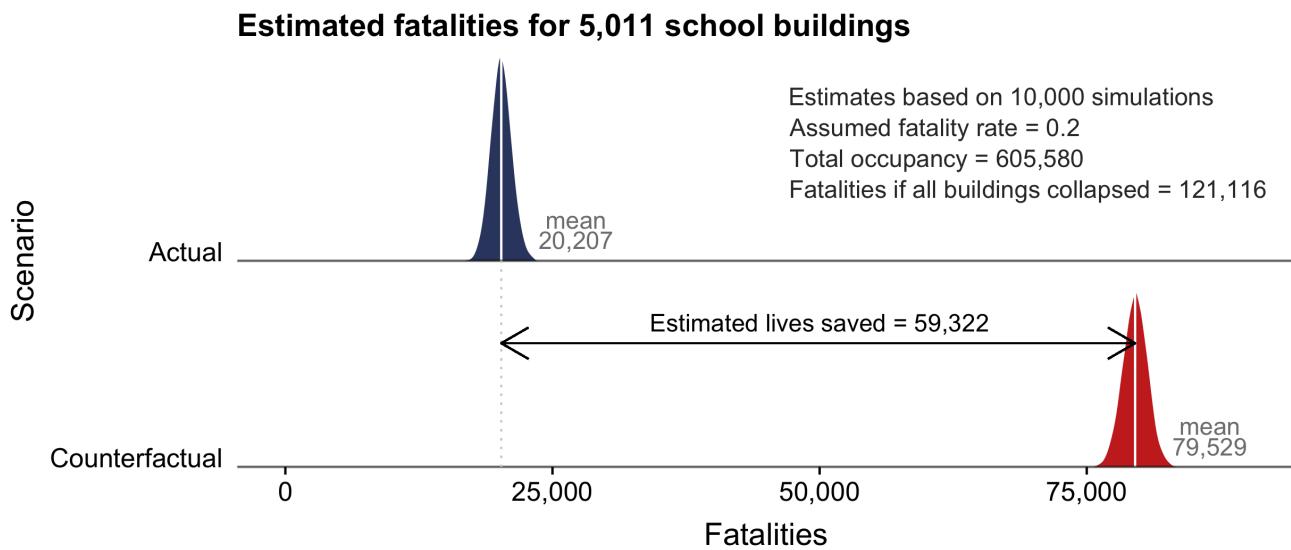


Figure 6. Distributions of estimated fatalities based on PGA values for 10% probability of exceedance in 50 years from Stevens et al. (2018). In the actual scenario, all 5,011 school buildings (See Figure 3) were completely retrofitted. For the counterfactual scenario, all school buildings were not retrofitted (i.e. the intervention doesn't exist). Our probabilistic analysis show that retrofitting all 5,011 school buildings will likely save 59,322 lives in the event of a 10% in 50 years shaking.

Figure 1.JPG

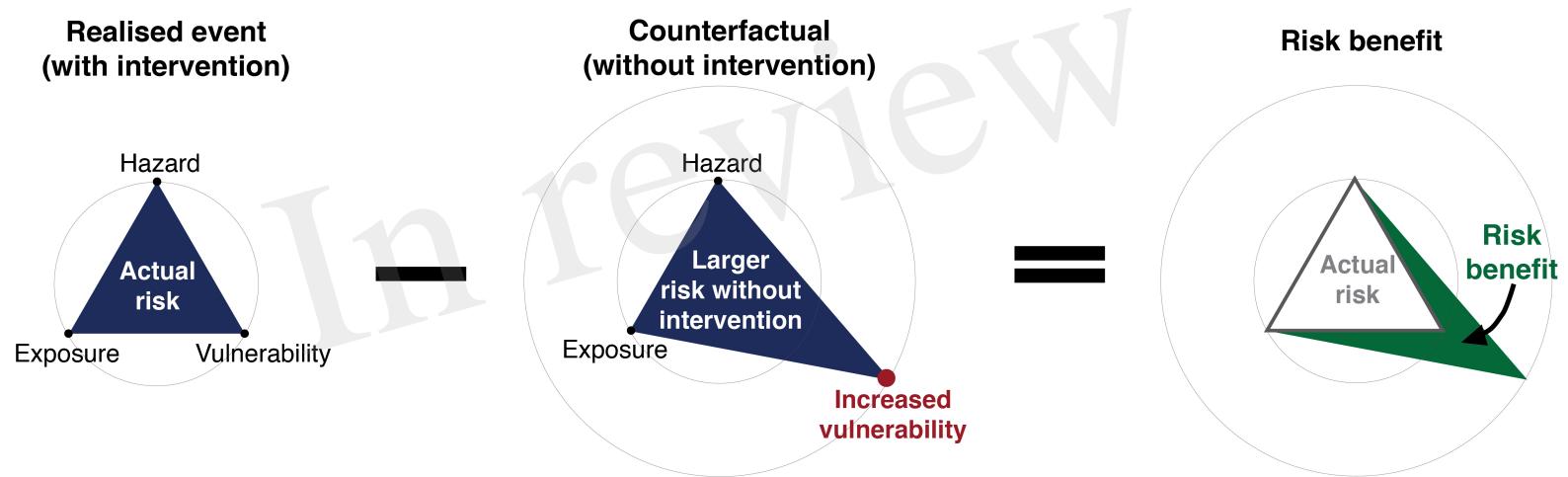


Figure 2.JPG

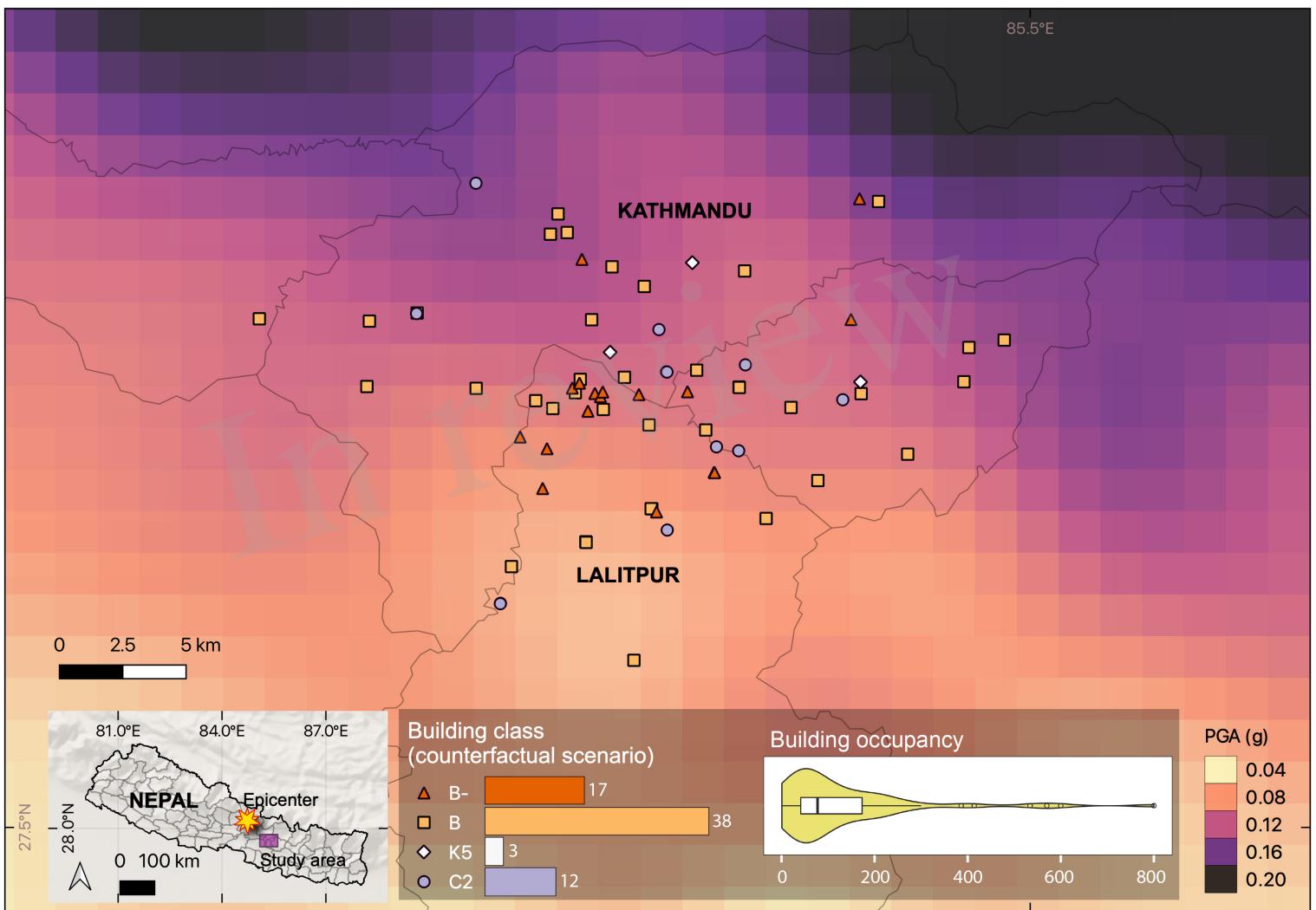


Figure 3.JPG

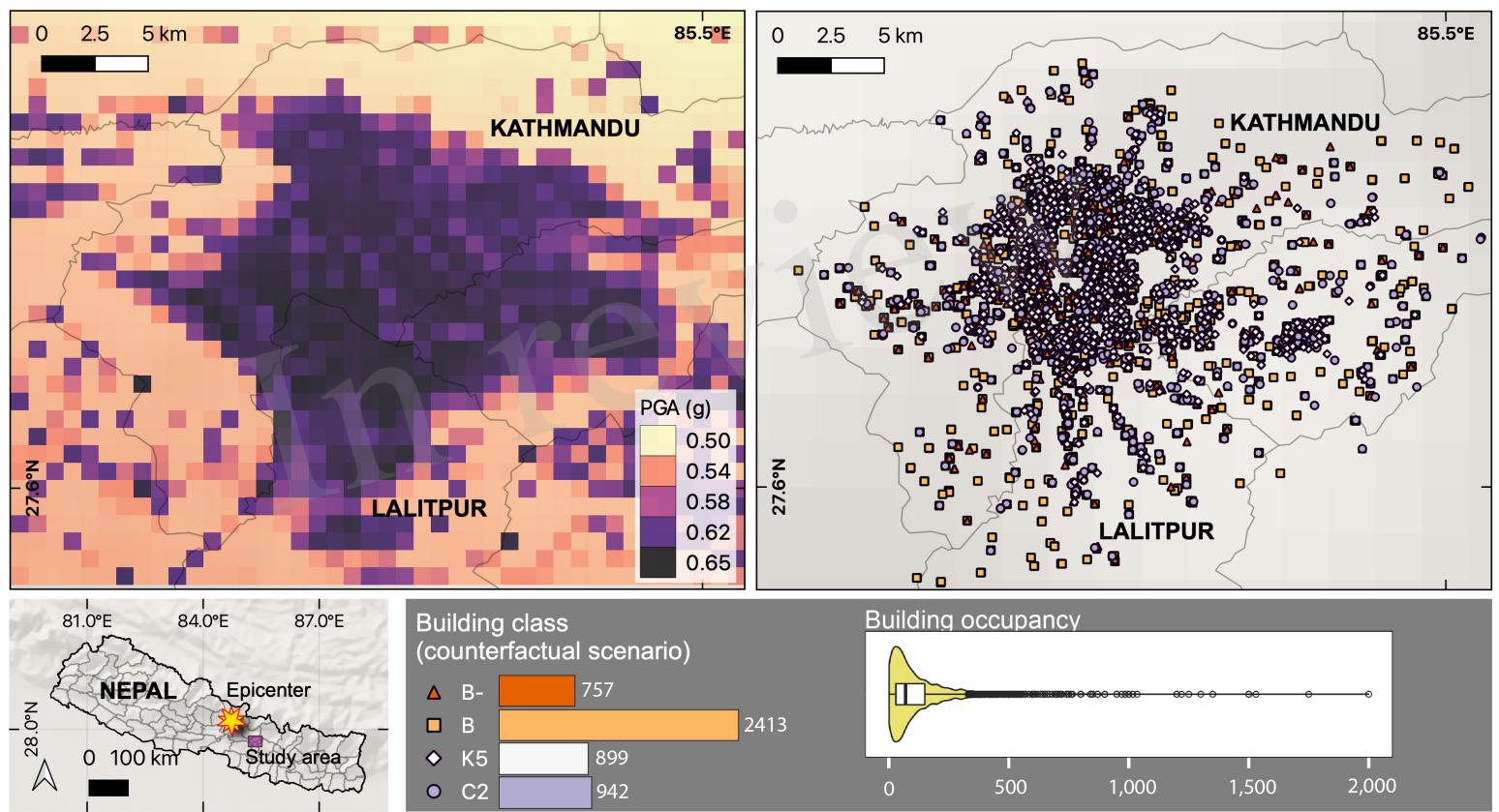


Figure 4.JPG

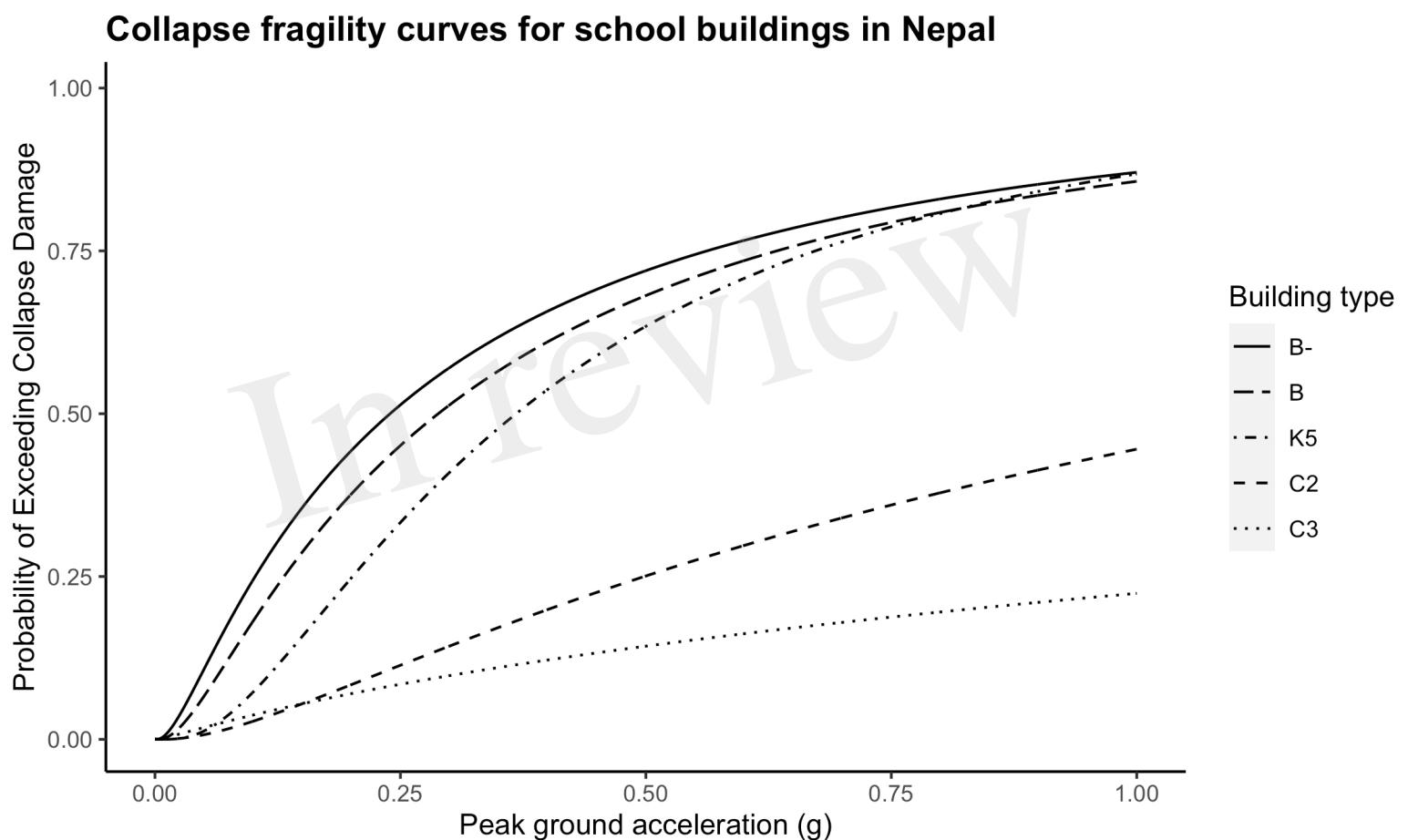


Figure 5.JPG

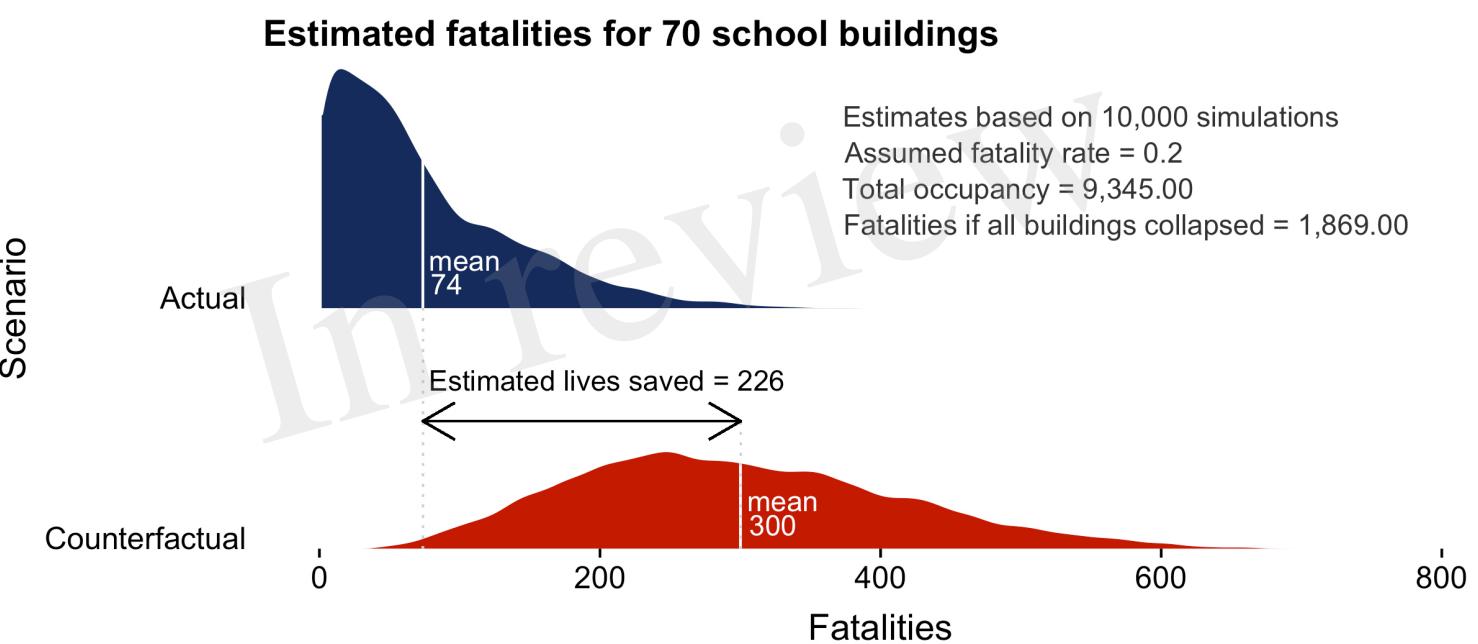


Figure 6.JPG

