Statistical Journal of the IAOS 31 (2015) 545–554
DOI 10.3233/SJI-150945
IOS Press

Predicting earthquake fatalities in Nepal

Elizabeth Newton[a,*], Javier Teran[b], Michiko Wolcott[c], Loren Velasquez[d], Dita Anggraeni[b], Yao Dai[e] and Brian Cocolicchio[f]
[a]*Statistics Without Borders, Wayland, MA, USA*
[b]*United Nations Office for the Coordination of Humanitarian Affairs, New York, NY, USA*
[c]*Statistics Without Borders, Dunwoody, GA, USA*
[d]*Statistics Without Borders, Chicago, IL, USA*
[e]*Statistics Without Borders, Tallahassee, FL, USA*
[f]*Statistics Without Borders, Suffern, NY, USA*

Abstract. The Nepal earthquake on 25 April 2015 resulted in over 8,000 deaths. The objective of this study was to develop a model useful in predicting fatalities following an earthquake in Nepal. The data for this study were obtained from the Humanitarian Data Exchange. This included MMI (a measure of the ground shaking resulting from an earthquake), population data and house construction data. Since most data were available only at the district level, we developed models for earthquake deaths at the district level. Zero-inflated negative binomial models were used to account for excess zeros and overdispersion in the fatality data. MMI was the strongest predictor of deaths and included in all models. Several models were developed and compared. The best models included primarily roof construction variables as predictors in addition to MMI. In contrast, a model including only wall construction variables performed poorly. For the best model, the Pearson correlation between predicted and observed deaths is 0.89.

Keywords: Earthquake, Nepal, fatality, model

1. Introduction

Nepal has a population of over 26 million people with 75 districts and 3,985 Village Development Committees (VDC's). The earthquake of 25 April 2015 resulted in over 8,000 deaths. With the epicenter in the eastern central portion of the country just east of Lamjung and approximately 80 KM northwest of the Nepalese capital of Kathmandu, the quake caused extensive damage and casualties in central and eastern Nepal as well as major landslides and avalanches. A strong aftershock followed on 12 May 2015, resulting in further casualties and damage.

Statistics without Borders (SWB), an outreach group of the American Statistical Association, and the Humanitarian Data Exchange (HDX), a part of the UN Office for the Coordination of Humanitarian Activities (UNOCHA), collaborated to analyze the fatality and casualty data from the quake. SWB and UNOCHA are both members of the Digital Humanitarian Network (DHN) and have previously collaborated on a number of humanitarian crises. The primary objective of this analysis was to gain insights about the factors in housing construction as well as population and demographic factors that are related to high levels of fatalities and casualties resulting from a catastrophic earthquake in Nepal. The analysis had a secondary objective of creating an index related to fatality level so that the emergency responders can effectively prioritize their response activities.

While there are existing indices available to aid with the response efforts, principally INFORM (Index for Risk Management) [1] which was leveraged in the response to this quake, the focus of this analysis was to identify factors that are statistically related to fatalities and to quantify their impacts specif-

*Corresponding author: Elizabeth Newton, Statistics Without Borders, Wayland, MA, USA. Tel.: +1 617 893 5544; E-mail: info@newtonstats.com.

Table 1
Population exposed at each level of MMI

MMI	Shaking	Population affected
I	Not felt	0
II–III	Weak	0
IV	Light	6,927,147
V	Moderate	4,035,675
VI	Strong	4,851,417
VII	Very strong	6,549,607
VIII	Severe	4,512,959
IX	Violent	0
X	Extreme	0

ically for an earthquake in Nepal. There are other models used to estimate earthquake casualties in near real time, including GDACS (Global Disaster Alert and Coordination System) [2], WAPMERR-QLARM (World Agency of Planetary Monitoring Earthquake Risk Reduction-EarthQuake Loss Assessment for Response and Mitigation) [3], PAGER (Prompt Assessment of Global Earthquakes for Response) [4,5], and NERIES-ELER (Network of Research Infrastructures for European Seismology-Earthquake Loss Estimation Routine) [6]. In addition, a recent paper by Chaulagain et al. [7] analyzed the impact of an earthquake in Nepal. However, the published estimates often have been at the national level and are intended to quantify overall losses rather than to be used as a search-and-rescue tool. To our knowledge, practical uses of country- or region-specific predictive models, statistically developed and designed to inform tactical operations have not occurred for Nepalese earthquakes.

2. Materials and methods

2.1. Datasets

All datasets used in this analysis are publicly available at The Humanitarian Data Exchange [8].

Nepal Earthquake Shakemap 4/25/2015, from the United States Geological Survey (USGS) [9]. A shakemap focuses on the ground shaking produced by the earthquake rather than the parameters describing the epicenter, taking into consideration the rock and soil conditions and the variation in the propagation of the seismic waves through the affected region. They are generated automatically by the USGS following moderate and large earthquakes. The USGS also generates an estimated Modified Mercalli Intensity Map (MMI) immediately following a quake based on instrumental ground motion recordings, and this was available at the VDC level for this analysis. The MMI, ranging from 1 (not felt) to 10 (extreme), measures the intensity of an earthquake at the earth's surface [10] rather than the energy released by an earthquake as measured by the Richter magnitude scale. Table 1 shows the Nepalese population exposed to MMI levels ranging from 4 to 8.

Nepal official figures for casualties and damage, from the Government of Nepal [11]. The official casualty figures (persons killed or injured) were collected by the Ministry of Home Affairs and the Nepal police. Available at the district level, the dataset was updated daily as new casualties were recorded and assessments conducted. For the purpose of this study, the data through 11 May 2015 was used in order to isolate further casualties caused by the aftershock of 12 May 2015.

Nepal Population Census 2011, from the Government of Nepal, Central Bureau of Statistics [12]. The census data at the VDC level, available as part of the baseline collection of the HDX platform, was leveraged for this analysis. A plot of the geographic distribution of the population, deaths, injuries and MMI in Fig. 1 shows that the greatest population density is in the southern districts. However, fatalities were highest in Sindhupalchok and the largest number of injuries was in Kathmandu.

Housing vulnerability, from the Government of Nepal, Central Bureau of Statistics (CBS) [13]. The CBS classifies houses based on construction materials for walls and roofs. In each district, the number of houses with each of five types of walls (mud-bonded brick or stone, cement-bonded brick or stone, wood planks, unbaked brick and bamboo) was recorded. Similarly, the number of houses with each of the six types of roofs (thatch-straw, galvanized iron, tile-slate, reinforced cement concrete (RCC), wood planks and mud) was recorded.

2.2. Exploratory data analysis

The distributions of numeric variables were explored using data summaries and histograms. Scatter plots and correlations were obtained to examine pairwise relationships among these variables.

2.3. Modeling

For this analysis, several potential outcome variables were available including deaths, injuries, total casualties (deaths plus injuries) and building damage. Since the context of the project is humanitarian response immediately following an earthquake, it made intuitive sense to focus on death and injuries. Of these, we focused on predicting deaths for several key reasons:

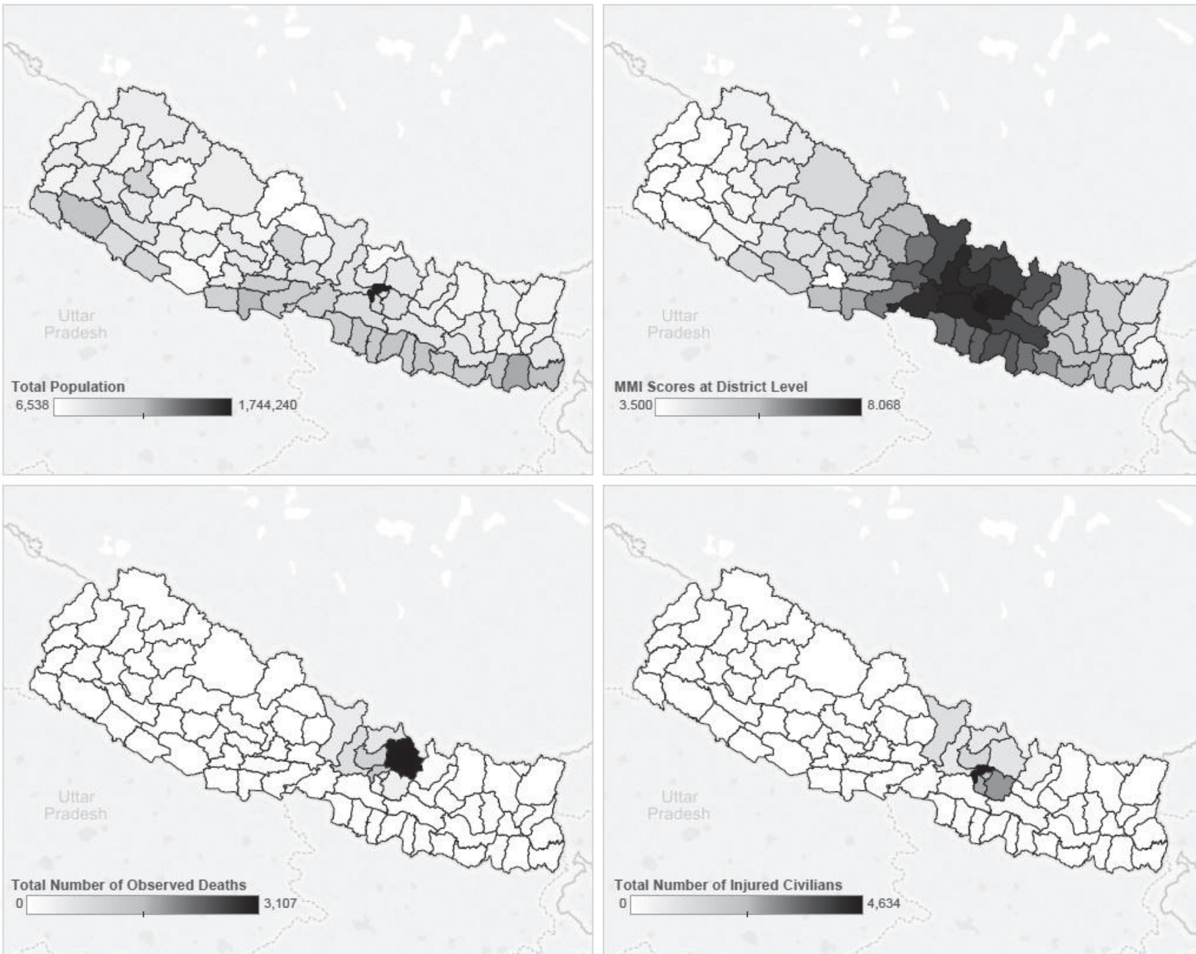


Fig. 1. Geographic distribution of population of Nepal, MMI, observed deaths and injuries.

– While injury information was available, the severity of the injuries was not recorded in the data, and an injury could conceptually include anything from minor cuts to critical injuries.
– What was initially an injury could eventually convert to fatality after a few days; therefore, in some cases injury may have been be only a transitional state.
– We chose to predict death counts, not death rate (death count divided by population count) or death density (death count divided by physical area). While death rate and death density are both useful measures for emergency response and could be modeled directly, they can also be derived by simply dividing the predicted death count by the appropriate denominator.

The MMI and the population data were available at the VDC level; however, most other information was available only at the district level. For this reason, models were developed at the district level, calculating the district-level population count and mean MMI.

Count data frequently is assumed to follow either a Poisson or negative binomial distribution. Of the 75 districts in Nepal, 44 (58.7%) reported no deaths, so zero-inflated Poisson and zero-inflated negative binomial models were considered. The Poisson model assumes that the variance is equal to the mean whereas the negative binomial model allows for overdispersion. Here the number of deaths at the district level had mean of 106.92 and variance of 168,701.5 which supports the choice of a zero-inflated negative binomial model.

This approach assumes that two processes that may result in a 0 outcome:

– Zero-inflation process: Excess zeroes are generated by whether or not the ground shook. If there is no shaking of the ground then no earthquake

Table 2
Data summaries for district level data

	Deaths	Injured	Population	MMI
Min	0	0	6,538	3.50
Q1	0	1.5	165,568	4.09
Median	0	7.0	271,061	5.20
Mean	106.9	238.2	358,357	5.43
Q3	5.0	30.5	522,341	6.82
Max	3,107	4,634.0	1,744,240	8.07

	wall_mud_ bonded_ bricks_stone	wall_cem_ bonded_ bricks_stone	wall_wood_ planks	wall_bamboo	wall_unbaked_brick
Min	1,192	18	10.0	1.0	0.0
Q1	17,432	1,060	267.5	106.5	9.5
Median	30,711	5,001	686.0	806.0	81.0
Mean	29,921	20,784	3,838.1	14,626.5	817.6
Q3	41,453	27,162	4,214.5	10,477.5	496.5
Max	66,442	350,265	45,611.0	118,224.0	23,294.0

	roof_thatch_ straw	roof_galvanized_iron	roof_tile_slate	roof_rcc	roof_wood_ planks	roof_mud
Min	4	163	36	5.0	13.0	0.0
Q1	4,541	2,938	2,950	427.5	113.5	0.0
Median	12,765	8,756	13,494	2,668.0	265.0	4.0
Mean	13,764	20,437	19,293	16,254.1	587.6	787.1
Q3	19,074	27,070	24,288	15,741.0	779.5	59.5
Max	62,465	132,048	95,137	337,404.0	5,820.0	16,782.0

deaths are possible. A binary model with a logit link estimates the probability of 0 deaths.

– Count process: Zeroes are generated by a counting process. A log-linear count model estimates the number of deaths.

MMI was included as a candidate predictor in both the count and zero-inflation portions of the model. Candidate predictors in the count portion of the model included the population and the counts of the various house construction types. Following the framework discussed by Austin and Tu [14], bootstrap resampling methods were used to find the best models. For each bootstrap sample, models for all possible three- and four-variable combinations of the 12 candidate predictors (11 house construction predictors and population), each also including the MMI as a predictor, were constructed. Using the Pearson correlation between the observed and the predicted deaths (referred to here as R1) as the selection criteria, the model with the highest R1 was chosen for each sample. Then, over all bootstrap samples, the variable combination most frequently chosen became the final model selected. With 12 candidate predictors, there were 220 possible three-variable models and 495 possible four-variable models. For comparison, models with only the wall construction variables and population were also considered, yielding 15 possible four-variable models from 6 candidate predictors.

Most of the analyses were performed with R statistical software [15]. The zero-inflated negative binomial models were fit with the zeroinfl function in the R package pscl [16,17], while visualization was done in R and Tableau [18].

3. Results

3.1. Exploratory data analysis

The district level data are summarized in Table 2. In general, the means are much greater than the medians indicating strong positive skew. This is confirmed in the histograms in Fig. 2 where the distributions of most of the variables show long right tails. Based on this, logs were taken of all predictors to obtain more symmetric distributions.

Spearman correlations presented in Table 3 show that deaths are strongly associated with MMI, roof_wood_planks, roof_galvanized_iron and negatively associated with roof_thatch_straw. Many of the house construction variables are highly correlated with each other.

Of the 75 districts in Nepal, 44 (59%) reported no deaths. At the other extreme, Sindhupalchok reported 3,107 deaths, Kathmandu 1,222 and Nuwakot 998. In 13 districts (17%), no injuries were reported. The lar-

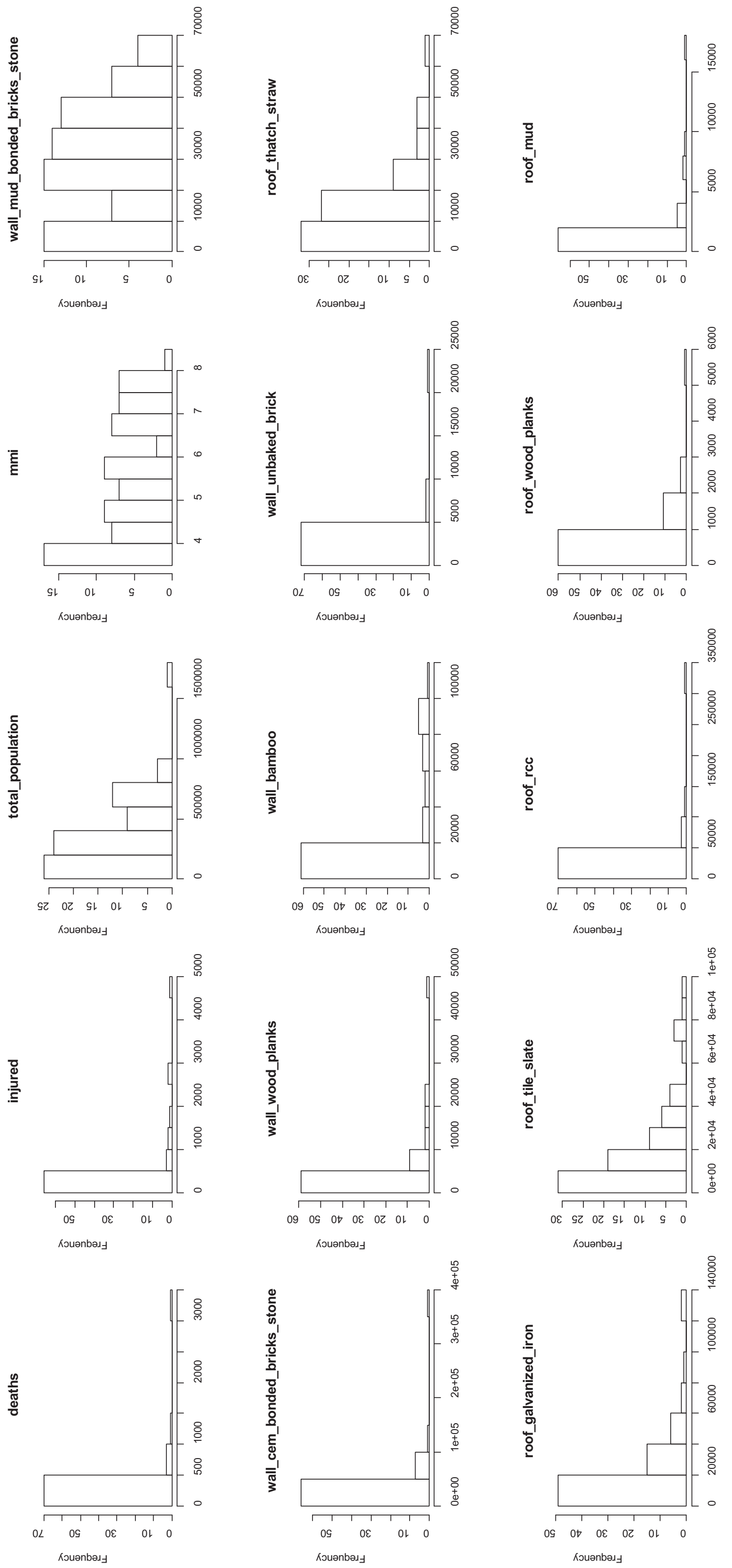


Fig. 2. Histograms of data.

Table 3
Spearman correlations

	deaths	ln_mmi	ln_wall_mud_bonded_bricks_stone	ln_wall_cem_bonded_bricks_stone	ln_wall_wood_planks	ln_wall_bamboo	ln_wall_unbaked_brick	ln_roof_thatch_straw	ln_roof_galvanized_iron	ln_roof_tile_slate	ln_roof_rcc	ln_roof_wood_planks	ln_roof_mud	ln_total_population
deaths	1													
ln_mmi	0.76	1												
ln_wall_mud_bonded_bricks_stone	0.24	0.1	1											
ln_wall_cem_bonded_bricks_stone	0.26	0.42	0	1										
ln_wall_wood_planks	0.1	0.21	-0.12	0.73	1									
ln_wall_bamboo	0.05	0.27	-0.23	0.72	0.85	1								
ln_wall_unbaked_brick	0.18	0.31	0.02	0.72	0.6	0.64	1							
ln_roof_thatch_straw	-0.14	0.01	-0.04	0.32	0.6	0.74	0.41	1						
ln_roof_galvanized_iron	0.32	0.37	0.4	0.61	0.47	0.48	0.48	0.27	1					
ln_roof_tile_slate	0.05	0.04	0.09	0.36	0.35	0.24	0.19	0.18	-0.17	1				
ln_roof_rcc	0.25	0.42	0.06	0.98	0.71	0.69	0.73	0.31	0.62	0.34	1			
ln_roof_wood_planks	0.46	0.49	-0.15	0.25	0.37	0.4	0.22	0.25	0.14	0.19	0.25	1		
ln_roof_mud	0.02	-0.22	0.14	-0.63	-0.57	-0.73	-0.53	-0.46	-0.43	-0.25	-0.64	-0.25	1	
ln_total_population	0.18	0.32	-0.02	0.6	0.45	0.45	0.52	0.18	0.22	0.34	0.58	0.35	-0.23	1

gest number of injuries was reported in Kathmandu with 4,634. However, as noted above, data on injuries is less accurate than data on deaths.

3.2. Modeling

In predicting deaths, zero-inflated negative binomial regression was used to account for excess zeros and overdispersion as discussed above. In bootstrap model selection, MMI was found to be the strongest predictor of deaths, and included in all models. Then we focused on models that included population and house construction variables as predictors in addition to MMI. MMI was the only predictor in the zero-inflation portion of the model.

In bootstrap model selection, out of 1,000 bootstrap samples, each testing all possible combinations of the 11 wall and roof construction predictors in addition to population, the most frequently chosen four-variable model included four roof variables: roof_thatch_straw, roof_galvanized_iron, roof_wood_planks and roof_mud. We refer to this as the Roof Model. This was chosen 82 times out of the 1,000 bootstrap samples (8.2%). The next most frequently chosen model included wall_bamboo, wall_unbaked_brick, roof_galvanized_iron and roof_wood_planks. This was chosen 59 times out of 1,000 (5.9%).

The most frequently chosen three-variable model included one wall and two roof variables: wall_bamboo, roof_galvanized_iron and roof_wood_planks. This was chosen 318 times out of 1,000 (31.8%). We refer to this as the Wall-Roof Model. The next most frequently chosen model included roof_thatch_straw, wall_unbaked_brick, roof_galvanized_iron and roof_wood_planks. This was chosen 82 times out of 1,000 (8.2%). Lastly we considered a model with only wall variables (and population) as predictors. In bootstrap model selection the final model included mud_bonded_brick_stone, cement_bonded_brick_stone, bamboo and population in addition to MMI as predictors.

Coefficient estimates obtained when the models are fit to the full data set are shown in Table 4. The Wall-Roof Model is slightly superior to the Roof Model with a lower AIC and a higher R1 (0.89 vs. 0.86). The Wall model, with an R1 of 0.49 compares poorly to other models in this analysis. In all of the models, the zero-inflation portion of the model indicated that MMI is negatively associated with the likelihood of 0 deaths, and in the count portion of the model, the MMI was positively associated with the number of deaths. The Roof Model indicated that thatch/straw roofs are negatively associated with deaths and that the other roof types contributed to higher deaths. Furthermore, the Wall-Roof and Wall Models indicated that bamboo walls are negatively associated with fatality.

Plots of observed deaths and deaths predicted by each of the models are shown in Fig. 3. For most districts, the predictions are fairly close to actual counts; however, for Sindhupalchok with the largest number of deaths (3,107), deaths are consistently underestimated by the models. Figure 4 shows the geographic distribution of observed and predicted deaths. The Roof model and the Wall-Roof model correctly identify Sindhupalchok as an area of highest fatality, whereas the Wall model predicts Kavrepalanchok to have the highest death toll.

4. Nepal earthquake hazard index

The use of scoring models, sometimes referred to as index models, has long been a staple as a tool for improving operational efficiency and effectiveness. Well-known examples of scoring models include credit risk scoring in which borrowers are evaluated in terms of their likelihood for repayment, marketing models in which the customers are evaluated in terms of propensity for some behavior (response to offers, attrition, etc.), and determination of priorities for allocating limited resources based on the relative likelihood of need for and/or impact of certain public services. The objective of these scoring models is to rank-order and prioritize a population of entities, individuals, events, or

Table 4
Coefficient estimates
Table 4a. Roof Model coefficients

Roof Model. Predictors are MMI and four roof variables.
Count Model Coefficients (negative binomial with log link)

	Estimate	Standard Error	Z value	Pr(>|z|)
Intercept	−21.648	6.006	−3.604	< 0.001
ln_MMI	7.768	2.151	3.611	< 0.001
ln_roof_thatch_straw	−0.746	0.219	−3.405	< 0.001
ln_roof_galvanized_iron	0.961	0.204	4.722	< 0.001
ln_roof_wood_planks	0.930	0.244	3.817	< 0.001
ln_roof_mud	0.360	0.120	3.000	0.003
log(theta)	−0.230	0.299	−0.767	0.443

Zero-inflation Model Coefficients (binomial with logit link)

	Estimate	Standard Error	Z value	Pr(>|z|)
Intercept	16.857	5.960	2.828	0.005
ln_MMI	−9.474	3.190	−2.970	0.003
R = 0.86	Log-Likelihood = 159.0 on 9 df		AIC = 336	

Table 4b. Wall-Roof Model coefficients

Wall-Roof Model. Predictors are MMI, one wall variable and two roof variables.
Count Model Coefficients (negative binomial with log link)

	Estimate	Standard Error	Z value	Pr(>|z|)
(Intercept)	−30.375	3.716	−8.173	< 0.001
ln_MMI	10.932	1.739	6.285	< 0.001
ln_wall_bamboo	−0.476	0.080	−5.992	< 0.001
ln_roof_galvanized_iron	0.929	0.168	5.537	< 0.001
ln_roof_wood_planks	0.939	0.233	4.041	< 0.001
Log(theta)	−0.313	0.307	−1.018	0.309

Zero-inflation Model Coefficients (binomial with logit link)

	Estimate	Standard Error	Z value	Pr(>|z|)
(Intercept)	13.119	8.201	1.600	0.110
ln_MMI	−7.970	4.386	−1.817	0.069
R = 0.89	Log-Likelihood = 156.5 on 8 df		AIC = 329	

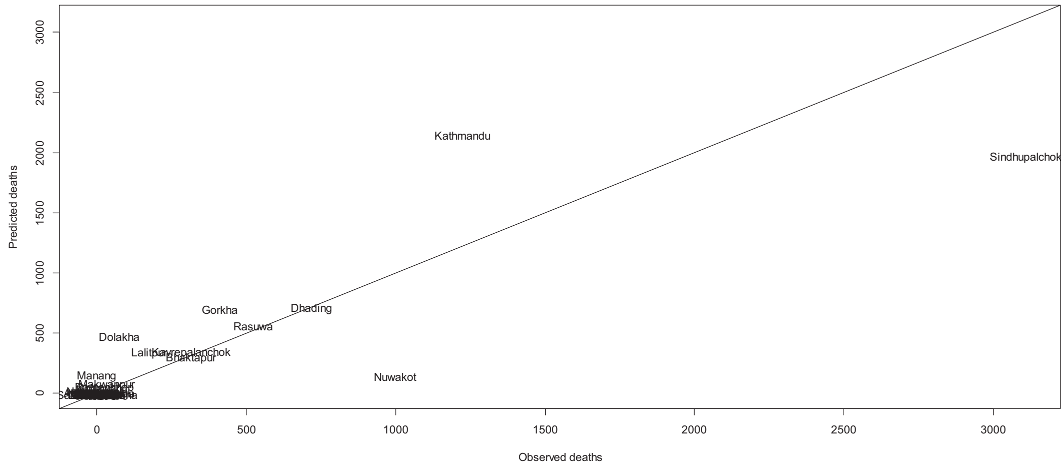
Table 4c. Wall Model Coefficients

Wall Model. Predictors are MMI, population and three wall variables.
Count Model Coefficients (negative binomial with log link)

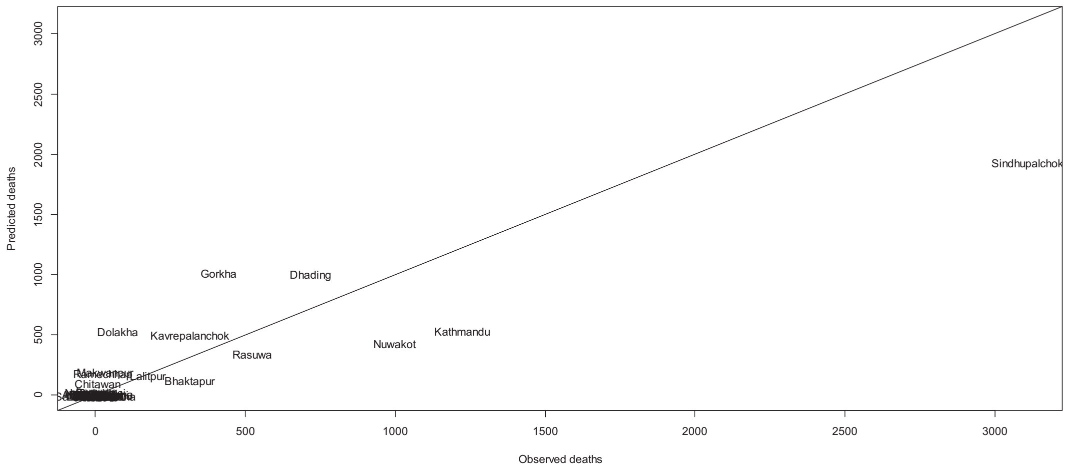
	Estimate	Standard Error	Z value	Pr(>|z|)
(Intercept)	−16.249	7.124	−2.281	0.023
ln_MMI	12.895	2.938	4.389	< 0.001
ln_population	−1.112	0.368	−3.026	0.002
ln_wall_mud_bonded_ bricks_stone	0.645	0.331	1.952	0.051
ln_wall_cement_bonded_ bricks_stone	0.484	0.247	1.962	0.050
ln_wall_bamboo	0.439	0.189	−2.328	0.020
Log(theta)	−0.722	0.283	−2.556	0.011

Zero-inflation Model Coefficients (binomial with logit link)

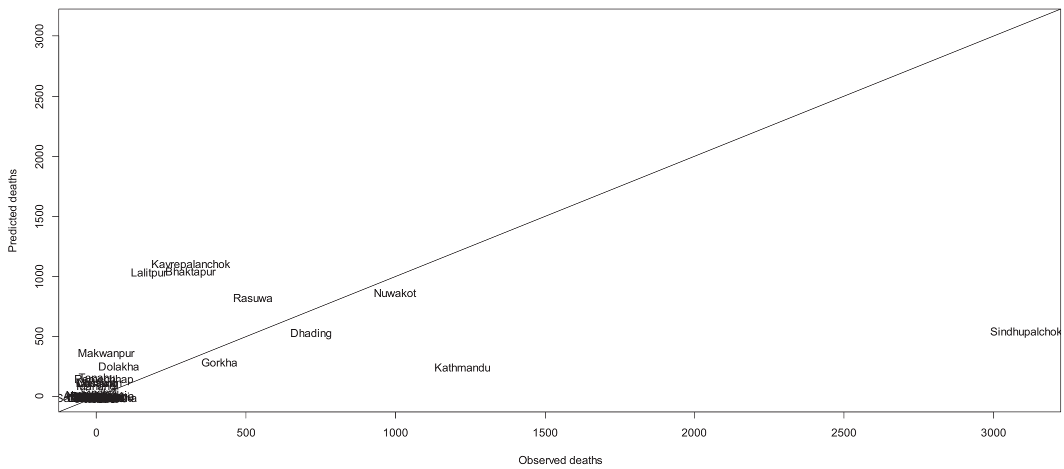
	Estimate	Standard Error	Z value	Pr(>|z|)
(Intercept)	17.651	6.876	2.567	0.010
ln_MMI	−9.923	3.643	−2.724	0.006
R = 0.49	Log-Likelihood=167 on 9 df		AIC = 352	



(a) Roof Model (Pearson Correlation=0.86)



(b) Wall-Roof Model (Pearson Correlation=0.89)



(c) Wall Model (Pearson Correlation=0.49)

Fig. 3. Plots of observed deaths vs. deaths predicted by each of the models.

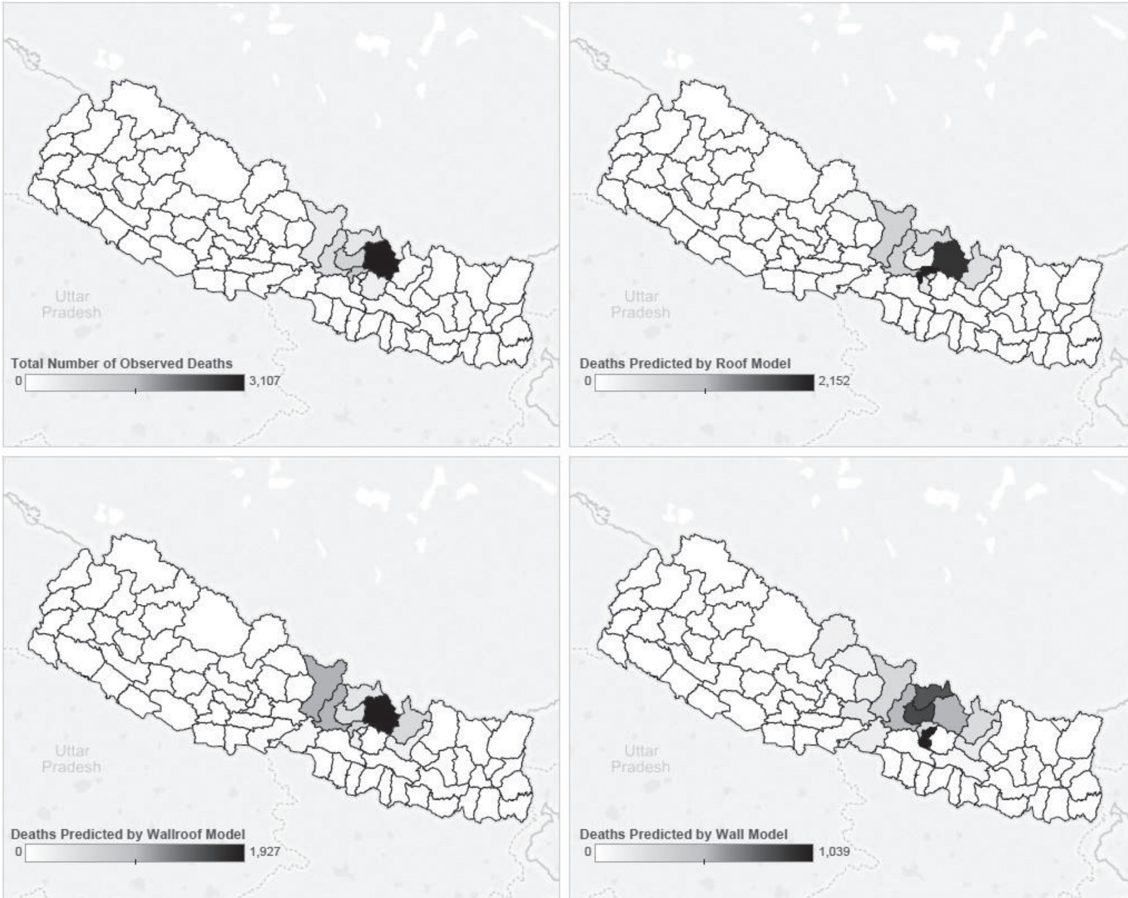


Fig. 4. Geographic distribution of observed and predicted deaths.

other items, rather than to estimate the exact magnitude of the outcome of interest. They are commonly constructed using statistical, machine-learning, and/or other empirical modeling methodologies, then the predicted values are transformed monotonically to a convenient scaling. Since the objective is rank-ordering, the scaling is simply a matter of choice.

The predicted death count was transformed into the Nepal Earthquake Hazard Index by taking its natural logarithm then scaling to values between 1 and 10. The predicted death rate (the predicted death count divided by the population count) and the predicted death density (the predicted death count divided by the area) were similarly scaled to take on values between 1 and 10, since the responders may consider the population size as well as the size of the area in addition to raw death counts.

Applying these indices, Sindhupalchok and Kathmandu are both identified as highest priority districts in terms of death counts (Death Count Index = 10), but only Kathmandu has a Death Density Index of 10 and only Manang has a Death Rate Index of 10. This is because Kathmandu has a much larger total population and a much smaller total area, making the likelihood of any given person dying lower but incidences of deaths per unit area very high, while the expected deaths for Manang is the highest compared to its population size. This may have implications in the planning and execution of the response efforts.

The indices allow substituting district-average MMI values with VDC-level MMI values. While the meaning of the predicted magnitudes is lost since other inputs remain at the district level, this allows the indices to capture some intra-district differences, enabling the responders to target smaller areas.

5. Discussion

The variables in the model ultimately selected tell us two key points:

The determining factor in whether there will be quake-related deaths is the degree of shake. While this is intuitively obvious – if there is no shake, there are no quake-related deaths – this also validates that the model is identifying factors that logically make sense.

The level of fatality is related primarily to the roof construction and to the degree of shake, and less so to the wall construction. This may be because certain types of roofs generally go with only certain types of walls. However, the wall construction variables by themselves were not adequate and often not very consistent in predicting deaths.

If more data become available at the VDC level, including not only casualty and house construction information, but also other factors known to be related to earthquake impacts, further refinement of these models may be possible. In the meanwhile, it is our hope that these models and the resulting indices prove useful in prioritizing emergency response efforts should another earthquake hit Nepal.

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Appendix

Conversion of predicted values to indices.

index_cnt = log (predicted);
if index_cnt $<$ -8.8640 then index_cnt = -8.8640;
else if index_cnt $>$ 7.3980 then index_cnt = 7.3980;
index_cnt = 1 + ((index_cnt − (−8.8640)) * (10 − 1))/(7.3980 − (−8.8640));
index_cnt = round (index_cnt, 0.1);

if total_population $\leqslant$ 0 then predicted_rate = predicted/1 * 1000;
else predicted_rate = predicted/total_population * 1000;
index_rate = log (predicted_rate);
if index_rate $<$ -14.1378 then index_rate = -14.1378;
else if index_rate $>$ 3.3592 then index_rate = 3.3592;
index_rate = 1 + ((index_rate − (−14.1378)) * (10 − 1))/(3.3592 − (−14.1378));
index_rate = round (index_rate, 0.1);

if area_final $\leqslant$ 0 then predicted_den = predicted/1 * 1000000;
else predicted_den = predicted/area_final * 1000000;
index_den = log (predicted_den);
if index_den $<$ -17.0052 then index_den = -17.0052;
else if index_den $>$ 1.3728 then index_den = 1.3728;
index_den = 1 + ((index_den − (−17.0052)) * (10 − 1))/(1.3728 − (−17.0052));
index_den = round (index_den, 0.1);