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TECHNICAL NOTE

Exploring geological and socio-demographic factors associated with under-five mortality in the Wenchuan earthquake using neural network model

Yi Hu[a,b], Jinfeng Wang[b]*, Xiaohong Li[c], Dan Ren[c], Luke Driskell[d] and Jun Zhu[c]*

[a]School of Earth & Mineral Resources, China University of Geosciences, Beijing; [b]State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing; [c]Sichuan University, Chengdu, P. R. China; [d]Department of Geography and Anthropology, Louisiana State University, Louisiana, USA

On 12 May 2008, a devastating earthquake occurred in Sichuan Province, China, taking tens of thousands of lives and destroying the homes of millions of people. Among the large number of dead or missing were children, particularly children aged less than five years old, a fact which drew significant media attention. To obtain relevant information specifically to aid further studies and future preventative measures, a neural network model was proposed to explore some geological and socio-demographic factors associated with earthquake-related child mortality. Sensitivity analysis showed that topographic slope (mean 35.76%), geomorphology (mean 24.18%), earthquake intensity (mean 13.68%), and average income (mean 11%) had great contributions to child mortality. These findings could provide some clues to researchers for further studies and to policy makers in deciding how and where preventive measures and corresponding policies should be implemented in the reconstruction of communities.

Keywords: under-five mortality; risk factors; neural network model; Geographic Information System (GIS); earthquake

Introduction

Child health development, as an important part of global economic and social progress, has received extensive attention from the international community. Maternal and child health is of great concern to many international health organizations. It reflects a society's overall standard of living and its level of development and life expectancy. In particular, under-five mortality is an important indicator of a country or district's health status. Reducing the under-five mortality rate by two-thirds between 1990 and 2015 is one of The Millennium Development Goals (MDGs) (Sachs and McArthur 2005).

One factor affecting under-five mortality, especially in undeveloped areas, is natural disasters, for example, earthquakes. On 12 May 2008, at 14:28 h local time, an earthquake registering 8.0 on the Richter scale hit the northwestern part of

Sichuan Province, China, with the epicenter recorded in Wenchuan County. It was estimated that more than 69,000 people died, with more than 374,000 seriously injured, and 18,000 reported missing. Among the large number of dead and missing were many children, particularly those aged less than five years old (Watts 2008). Therefore, it heavily influenced the local under-five mortality rate, making it more difficult to reach MDGs.

Psychologically and physically, children under five years of age are largely dependent on their families and lack the ability to protect themselves in response to sudden disasters. Consequently, they are more vulnerable than adults to natural disasters like earthquakes, especially children from poorer areas who have a poor quality of life and a poor residential environment. As part of effects to understand the epidemiological characteristics and spatial patterns of child mortality and to explore the preventive measures that could be employed, potential factors that may be associated with earthquake-related child mortality need to be identified. In this study, we first identify and map the spatial distribution of the under-five mortality at the township level, and then report on relevant physical and human factors, such as earthquake intensity and population density. Finally, we employ a neural network model to assess the association between child mortality and those factors.

Methods

Statistical model

Numerous risk assessment methods for deaths and injuries have been proposed. Usually, an epidemiological method is used to measure risk factors. Ellidokuz et al. (2005) used a multivariable logistic regression model to analyze risk factors for deaths and injuries in an earthquake in Afyon, Turkey. A univariate and multivariate analysis model was used by Armenian et al. (1997) for the same purpose for an earthquake in Armenia. However, all the models or methods used above involve many assumptions, such as assuming response variables to follow certain distribution (e.g., normality, binomial and etc.) and to be independent and identically distributed, and violation of such assumptions can have a major impact on model validity. In addition, when dealing with nominal variables that have many categories, the traditional models are problematic (Allen 1997). Therefore, there is a need to develop suitable, if not better, techniques for assessing the risk of child mortality in the present study.

Neural networks are computer-based algorithms and can be trained to recognize and categorize complex patterns (Bishop 1995). They offer a novel approach to extracting the implicit interrelationships between various parameters without any assumptions or restrictions with respect to explanatory and response variables. Moreover, they can recognize highly non-linear associations between independent and dependent variables. These kinds of associations are known to be difficult to model using classical methods (Bourquin et al. 1998). A multilayer perceptron (MLP) was used in this study. Further details of this modeling approach are given in the Appendix.

Description of the study area

The study area includes 21 earthquake-hit counties (454 townships) confirmed by the Ministry of Civil Affairs, located in northeastern Sichuan Province, stretching across the Qingchuan landmass and Sichuan Basin (Figure 1). The topography decreases
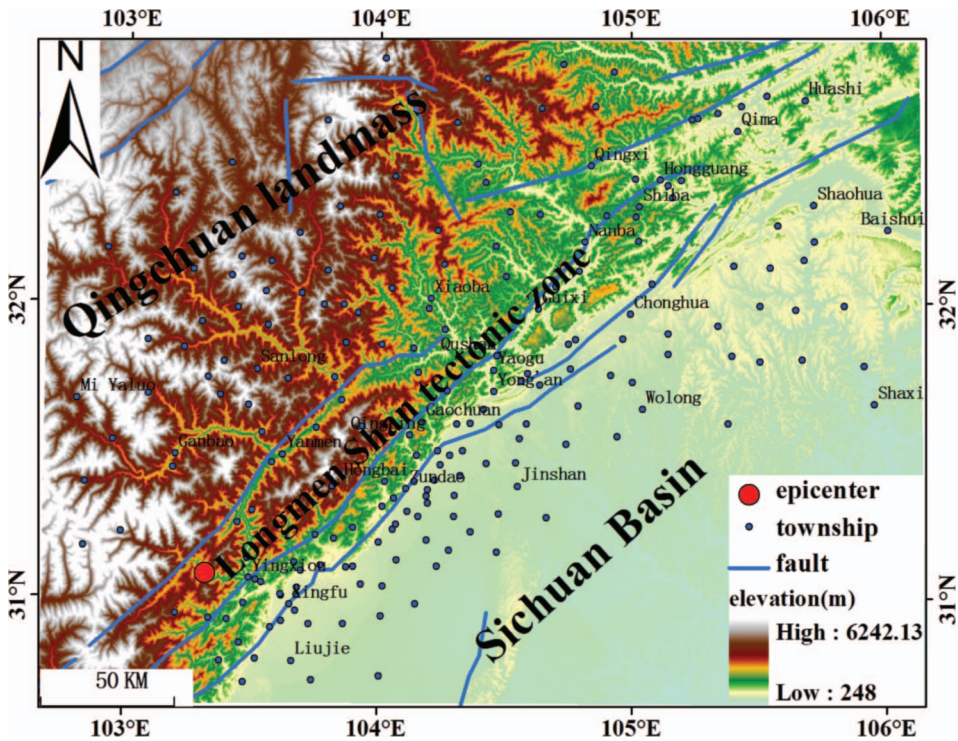
Figure 1. Distribution of 454 earthquake-hit townships in the Wenchuan earthquake (Information office, China 2008).

from the northwest (with an altitude of over 3,000 m) to the southeast (below 1,200 m). Mountains dominate the western landscape, with lower hills in the east and piedmont alluvial plains in between.

The population of the study area is characterized by an uneven distribution, with a greater population in the east than in the west. The plains have a higher population density of 600–800 persons per square km, while the mountainous areas have lower levels at 150–300 persons per square km. The economic situation is stronger in the Longmen Shan Qian area (10 counties), with a GDP of 16,053 RMB per capita, compared with the area located in west with a GDP of 9,315 RMB per capita (11 counties).

Data of earthquake-induced mortality

The National Office for Maternal and Child Health Surveillance provided under-five mortality data collected at the township level in the Wenchuan earthquake. A total of 934 earthquake-related deaths for children under five years of age were finally confirmed in the study area, with 683 cases of direct death and 251 cases of indirect death. The 934 confirmed deaths were distributed among 115 administrative townships in 21 counties of Sichuan Province, which also includes 339 other townships that did not experience any earthquake-related deaths. The spatial distribution at the township level of earthquake-related under-five mortality is shown in Figure 2.
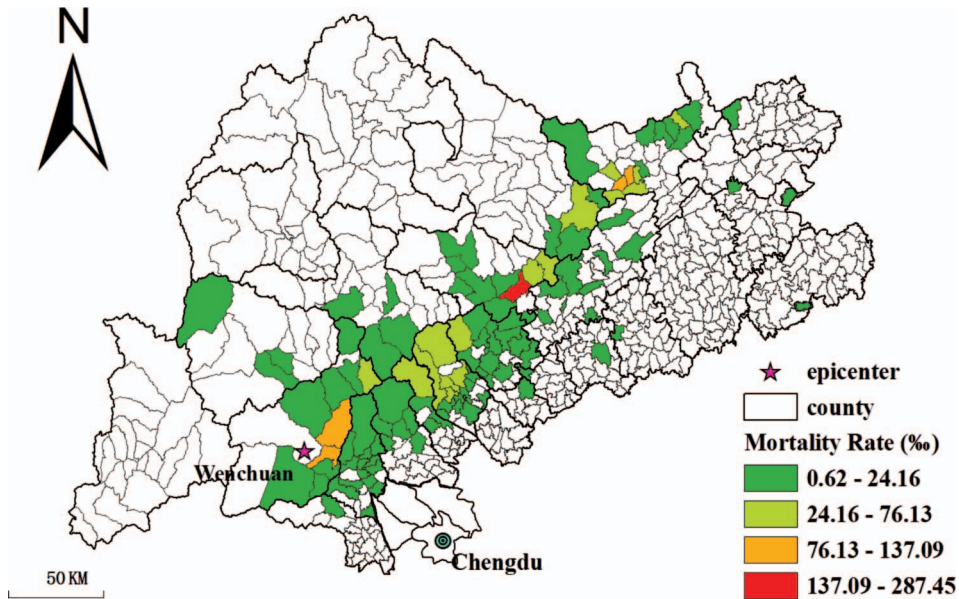
Figure 2.   Under-five mortality rate at the township level in the Wenchuan earthquake. Thematic categories are based on the Jenks natural breaks method.

Determinants of under-five mortality and their proxies

The key determinants leading to child mortality (direct deaths and indirect deaths) are diverse and complex, and include structural failure, falling objects, fire, landslide, and car accidents. It is difficult to analyze those determinants directly as risk factors. For example, analyzing structural factors like building materials, number of storeys, and the age of the structures, can account for direct deaths but not indirect deaths. In addition, it would be awkward to treat fire or car accident as risk factors and they cannot account for direct deaths. These complex determinants actually operate through at least two geographic layers that are easy and convenient to implement when used in a geographic information system (GIS) environment. These layers can be grouped as follows:

(1) Physical factors that are spatially distributed. For instance, the magnitude and intensity of an earthquake can determine the loss of life and impact on the economy in one area or district, and the type of topography, such as a hill or mountain, can determine whether secondary geological disasters may happen afterwards, causing further destruction.
(2) Human factors that are spatially distributed. Economic conditions can determine structural characteristics and the standard of materials used on houses, which in turn affect resistance to earthquake damage. Economic conditions also impact on the available medical services in the aftermath of earthquakes, which can provide instant aid to reduce the loss of life.

Figure 3 illustrates a conceptual framework that involves the direct determinants and their explicit geographical proxies. Through the study of these two geographic layers,
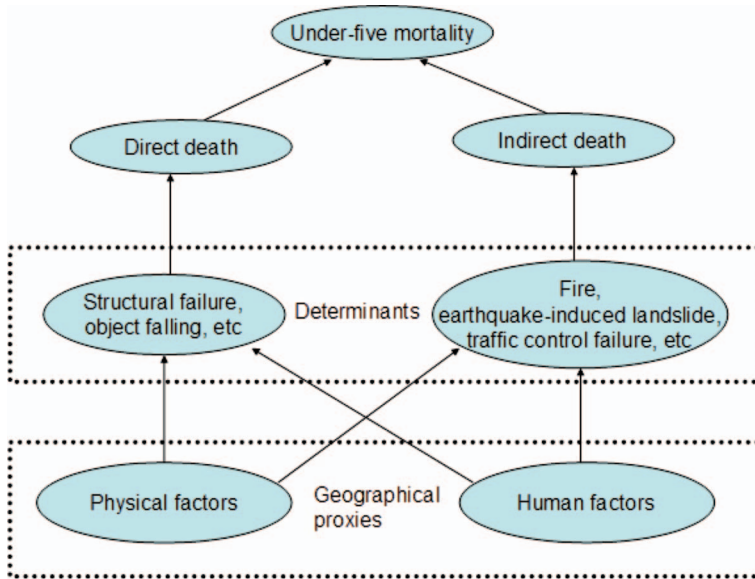
Figure 3.   Relationship between determinants of child mortality and their proxy variables.

we can have a better understanding of the local environment in the earthquake-hit area and be better equipped to conduct our ecological study to help solve the social and environmental problems effecting child mortality. Although the ecological analysis is subject to errors, such as ecological fallacy (Washio et al. 2008), it is appropriate for hypothesis generation and provides essential information need before moving on to the more rigorous study designs about child mortality, e.g., individual-level study.

Physical proxies, particularly geological proxies, were collected: Average elevation, average topographic slope, distance from township to fault, geomorphology, and earthquake intensity; human proxies, particularly socio-demographic proxies, included population density, number of migrant workers, and average income.

The topographic elevation of the study area was obtained using a Digital Elevation Model (DEM) (Figure 1). The DEM used in this study was derived from The Shuttle Radar Topography Mission (SRTM), an international project spearheaded by the U.S. National Geospatial-Intelligence Agency (NGA) and the U.S. National Aeronautics and Space Administration (NASA). The average elevation of each township was calculated by averaging the elevation values of all elevation points within each administrative area.

Slope is defined by a plane tangent to a topographic surface, as modeled by the DEM at a point (Burrough 1986). Slope presents the percent change in elevation over a certain distance. The output slope can be calculated as either the percent or degree of slope. In this study, degree of slope was chosen. Like average elevation, the average slope of each township was acquired by averaging the slope values of all slope points within each administrative area.

Geomorphology data were provided by the state key Laboratory of Resources and Environmental Information Systems (LREIS) from the Institute of Geographic

Sciences and Natural Resources Research (IGSNRR), Chinese Academy of Science (CAS). The geomorphology of the study area can be divided into seven classes: Plain, terrace, hill, low-relief mountain, middle-relief mountain, high-relief mountain and extremely high-relief mountain. Geomorphology class at the township-level was implemented with GIS using an overlay analysis.

Earthquake intensity in the study area was determined using an official Chinese Earthquake Administration Modified Mercalli Intensity (MMI) scale map. The MMI scale is divided into 12 continuous categories (Wood and Neumann 1931). The lower degrees of the MMI scale generally deal with the manner in which the earthquake was felt by people. The higher degrees are based on observed structural damage. The Wenchuan earthquake MMI in the study area ranged from VII–XI. The distribution of MMI values within each township was determined using a GIS overlay. For each township, areas categorized with different MMI values were computed. From this area distribution, an area-weighted averaged MMI for each township was estimated.

There are a series of thrust faults that affect the study area (Figure 1), for example, the Wenchuan-Maoxian, Yingxiu-Beichuan, and Anxian-Guanxian faults. The earthquake intensity zones are elliptical, with these faults being major axes. Townships in the same intensity zone suffered the same devastating power described above, though some are closer to the epicenter. In addition, geologically, the rupturing of the crust around those faults was the main cause of structural damage. Consequently, we assumed that studying distance to faults to be more meaningful than studying distance to the epicenter. Using a GIS environment, administrative boundaries of townships in the study area were represented by polygons. The distance from town to fault was determined by vertical distance from the centroid of each polygon (township) to its nearest fault.

'Migrant workers' refers to people that have left their hometowns (within our study area) to look for jobs in developed areas (e.g., cities where they hope to financially be able to support their families). The number of migrant workers in each township was obtained from the Evaluation of Bearing Capacity of Resources and Environment (EBCRE) database, which was set up in 2009 by IGSNRR, CAS, using the national reconstruction plan.

Data with regard to population density and average income at township-level were also sourced from the EBCRE database.

Data analysis

The manipulation and calculation of the proxy variables were implemented using ArcGIS 9.2. A collinearity diagnosis was conducted among explanatory variables using SAS8.0 to detect whether any variable was collinear with other variables. This ensures that the risk factors contain different information about the response variable (mortality rate) and precise impact of one risk factor on child mortality controlling for others. Two indicators were employed: Eigenvalues of the X'X (proxy variable) matrix and a condition index, which shows the square roots of the ratio of the largest eigenvalue to each individual eigenvalue.

In a neural network two sets of data are required. One set, the "training set", is used by the learning algorithm to establish an appropriate set of network weights,

which accurately represent associations between input and output. The ability of the network to generalize is then tested on a fraction of data that has not been shown to the network before, but for which the outcomes are known. This data set is known as the "test set" and provides an objective analysis of model performance. Data from 364 townships (80% of the townships) were used randomly as training data to construct a network, and the remainders were used as test data to measure the accuracy of the network. The performance of the neural network was evaluated by Root-Mean-Square (RMS) error between network outputs and targets, and by a correlation coefficient that measures how well the predictions agree with the targets. A correlation coefficient of 1 or −1 indicates perfect correlation, and values close to 0 indicate that little or no correlation exists between network predictions and targets. To fully use the data during network construction, we randomly divided the mortality data into a test and training set 100 times, and then the average RMS and correlation across all 100 trials were computed.

A sensitivity analysis was performed after a network was near its fully trained state, in which the relative contribution of each input variable to the output was examined. Sensitivities are determined in training set by cycling each input for all training patterns (cases) in the final network solution and computing the effect on the network's output response (Cathcart and Materazzo 1999). This analysis helps to identify the most important risk factors to child mortality. Qnet2000 by Vista Services, Inc. was used for neural network construction and performance evaluation.

Results

Collinearity diagnostics for all variables, except the geomorphology variable (seven input variables), show (as presented in Table 1), that no collinearity exists in those variables, taking into consideration the suggestion of Belsley et al. (1980) that weak dependencies may affect regression estimates when the condition index is around 10.

Table 1. Collinearity diagnosis of input variables for neural network.

Number	Eigenvalue	Condition index
1	2.65	1.00
2	1.33	1.41
3	1.01	1.62
4	0.96	1.66
5	0.56	2.17
6	0.34	2.80
7	0.14	4.32

The average RMS errors for training and test data are both 0.03 and the average correlation coefficients are 0.86 and 0.70, respectively. As illustrated in Table 2, the average slope variable had the greatest contribution (mean 35.76%). It was followed by geomorphology (mean 24.18%), earthquake intensity (mean 13.68%), and average income (mean 11.00%). The remaining variables had low contributions to child mortality.

Table 2. Average contribution of factors on under-five mortality in the Wenchuan earthquake (Information office, China 2008).

Risk factors	Percent contribution (%)
Population density	2.07
Number of migrant workers	1.75
Average income	11.00
Average elevation	5.62
Earthquake density	13.68
Distance from town to fault	5.94
Average slope	35.76
Geomorphology	4.53
	1.71
	2.49
	3.20
	7.09
	5.16

Discussion and conclusion

The utility of neural network models lies in the fact that they can be used to infer a function from observations and also to use it. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical. Considering the complexity of mortality in earthquakes (diverse determinants of child mortality), the neural network model was used in this study. We believed that this approach has more advantages over traditional regression. The estimator method of neural network do not require strict assumptions to be imposed (e.g., linearity and normality), and as such, models derived using this approach can be more reliable. Additionally, a neural network has the ability to detect, on its own, all possible linear or nonlinear interactions between the model parameters (Hajmeer and Basheer 2003). Neural network techniques have been extensively applied to a variety of areas in health services research, such as clinical diagnosis (Dorffner and Porenta 1994), HIV-structure analysis (Andreassen et al. 1990), image analysis (Dawson et al. 1991), predication of cancer (Floyd et al. 1994), and prediction of length of stay in a hospital (Lowell and Davis 1994).

Of more interest is which input variable (proxy risk factor) has the greatest role in the outcome of output response (mortality). As illustrated in Table 2, the average slope variable was identified as the most important factor affecting child mortality (mean 35.76%). One possible explanation would be secondary geological disasters triggered by earthquakes. Slope of topography is commonly regarded as directly related to landslide initiation; it is an important factor in landslide hazard analysis, and mudslides usually start on steep slopes and can be activated by natural disasters (Chen and Wang 2009). This indicates that slope can be an agency that reflects secondary geological disasters following an earthquake. The earthquake had a great impact on the local geological environment, resulting in large-scale secondary disasters in Sichuan Province, such as landslides, mud-rock flows, and quake lakes, all of which resulted in many indirect deaths (as defined in this study). Preliminarily judging, about a third of the whole Wenchuan earthquake losses were not by the direct result of the earthquake, but by the secondary geological disasters (Liu and Sun 2009). In addition, slope is an indicator of topographic relief (Kuhni and Pfiffner 2001). Areas with a steep slope are usually characterized by high relief, such as

mountains, valleys, or gorges. The residential buildings in those areas were extremely vulnerable to the earthquake, which resulted in many direct deaths (as defined in the present study). One reason for such poor housing conditions is that local residents are unable to afford stronger homes because of the economic conditions described earlier. In addition, from a geological engineering perspective, it is difficult to find appropriate sites for building safe houses in such areas.

The second most important proxy factor affecting child mortality is geomorphology (mean 24.18%). Of all geomorphology types, mountainous areas (mean 15.45%) had the highest correlation to child mortality, which supports the proposition that average slope contributes to mortality, while terrace areas (mean 1.71%), hill areas (mean 2.49%), and plain areas (mean 4.53%) showed low correlations. Earthquake intensity follows as the next most important factor (mean 13.68%). The magnitude measured on the MMI scale for the study area grew from VII–XI. This represents measurements of the earthquake's impacts at different sites: The larger the magnitude is in a particular region, the greater its destructive power. Townships that measured high intensity magnitudes also had high rates of mortality ($\gamma = 0.50$, $p = 0.01$).

The average income within townships (mean 11.00%), which reflects the living conditions of local people, is the next factor in terms of impact. A higher income enables individuals to respond to risks by employing additional, costly precautionary measures, thus, providing greater protection for children. For example, families in wealthier areas lived in houses constructed with better materials, which made them more resistant to earthquake damage. Moreover, people living in undeveloped areas received less education and were less able to make good choices with regard to safe construction practices and building placement. Income plays an important role in mitigating losses from disasters. Several researchers (Burton et al. 1993; Horwich 2000; Kahn 2005) have noted the importance of economic development in reducing vulnerability.

Other variables had relatively low contributions (from 1.71–5.94%). Surprisingly, the number of migrant workers, which was considered to be strongly related to children, had little contribution (1.75%) to child mortality. The migrant worker factor was taken into account because not only does it play a significant and unique role in China, but it is closely related to the circumstances of children. China's economic boom and work-orientated society is witness to huge inequalities between the salaries paid to workers in the cities and countryside. Many villagers, particularly young adults, chose to travel to the larger towns in search of work, leaving their children behind and rarely seeing them again. These children are usually taken care of by their grandparents. Children's parents can provide them greater support and protection, both psychologically and physically, in emergency situations such as earthquakes, compared with their elderly grandparents who are also vulnerable in earthquakes. In this study, however, little correlation between migrant workers and child mortality can be found. This left an area in which a more in-depth study, e.g., individual-level study, could reveal whether the presence of parents affects survival of children in earthquakes. Distance to the fault was a further variable with a low contribution to child mortality. Previous studies showed that fault (Pai et al. 2007) and population density (Gutierrez et al. 2005) were significantly associated with mortality rate. The results of our study, however, showed that the distance from the fault and population density had little correlation with child mortality.

The somewhat low average correlation coefficient (0.70) of the test data probably indicates that available the risk factors were not sufficient to characterize child mortality. It also reflects the intrinsic fuzziness of the data associations and indicates

the absence of important variables from the initial data set (Kaufmann et al. 1997). Our study only focused on some geological and socio-demographic factors, which indicates a limitation of the study, and this requires more factors to be considered in further studies, such as access to major transportation routes and major medical centers which certainly affect the timely delivery of emergency services and thus mortality. Another reason for the low correlation coefficient may be due to the lack of sufficient townships included in this study. Effective neural network models require an adequate number of training examples (Kaufmann et al. 1997). A larger data pool may result in a more accurate model. The final size of the training data in this study, which was limited by the number of townships in the study area, may have affected the accuracy of the predictive model. A further limitation of this study is that proxy factors used in this study provide only indirect measures of determinants of child mortality and associations between proxy factors and child mortality found by the present modeling approach reflect statistical relationship rather than causal relationship.

Despite some limitations, the findings in this study can still have important implications for both researchers and policy makers. For researchers, the results of this ecological study can provide the opportunity for further, more careful studies conducted at an individual level (case study), where certain factors can be studied in depth; for policy makers, the findings can provide some clues as to how and where new townships should be reconstructed after earthquakes. Specifically, the slope, reflecting local topographic relief, is a top priority when considering new sites for habitation. According to the Evaluation of Bearing Capacity of Resources and Environment Project, IGSNRR, CAS (Fan 2009), a topographic slope of 15–25° was the threshold for landslides and mudrock flows in Sichuan Province. Therefore, it would be safer to choose new township sites with a topographic slope below 15°. Furthermore, consideration of the slope of land is important not only to minimize risks from natural hazards like earthquake and landslides, but to reduce the construction costs and impacts of proposed development on natural resources such as soil, vegetation, and water systems. Considering the effects of an earthquake on humans, natural objects, and man-made structures, local government should be aware of the quality of residential structures to ensure the structures' resistance to earthquakes registering at least 8.0. Special attention should be paid to people residing in mountainous areas. Engineering professionals could be sent to those areas to help locals choose appropriate building sites and to build their houses. Moreover, the finding that income is another important risk factor further supports the necessity for local governments to concentrate on the improvement of local economic conditions and income.

Acknowledgement

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Appendix

Introduction to the Neural Network model

To date, most of the neural network applications in science and engineering have focused on the use of the back-propagation learning algorithm, which is also called multilayer perceptron (MLP) network, because of the simplicity of the methodology and its precisely defined and understood learning laws and its distinguished ability to generalize. As shown in Appendix Figure 1, the architecture of a back-propagation neural network is composed of an input layer, one or more hidden layers, and an output layer. The input layer nodes feed the input values into the rest of the network. Connections between layers are bi-directional. Data value move from inputs through the hidden layers to the outputs during feed forward operation. During learning, error corrections are propagated back through the network starting from the output nodes and running upward through all hidden nodes from the bottom to the first hidden layer.
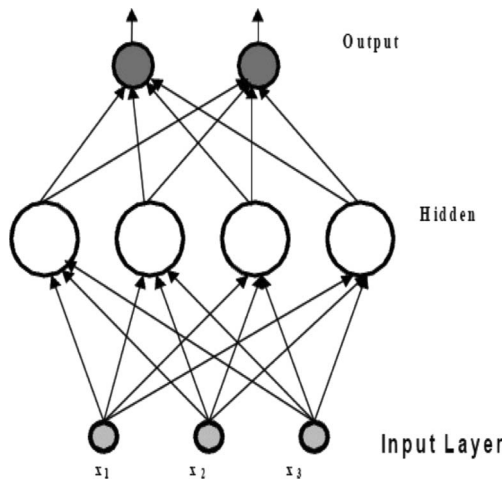
Appendix Figure 1.   Neural network architecture.
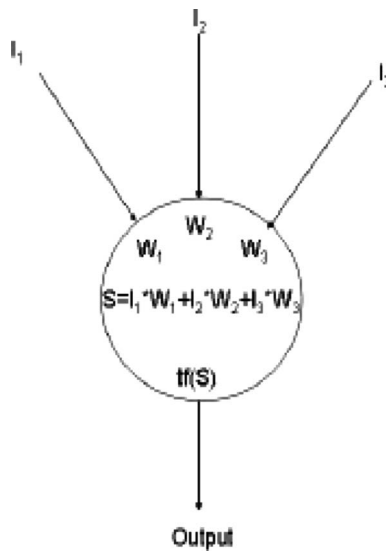
Appendix Figure 2.   Neural network node.

All hidden and output nodes in the network have the structure shown in Appendix Figure 2. During feed forward operation, the node first calculates the sum of all inputs times their weights. A transfer function is then applied to the sum. This function transforms the output into a number between zero and one. Several functions can be used which have either a ramp, bell or modified S-shaped curve that runs asymptotically along the X-axis approaching either the maximum or minimum value. The type of transfer function is manually selected during network construction while the weights for each input connection are calculated during the learning process described below. All inputs must also be scaled to values between zero and one. Outputs, which are all values between zero and one, must be scaled in the reverse direction from a decimal value to the actual value.

Construction of neural networks is primarily a manual operation. Developing good neural networks can be as much an art as it is a science. The model builder must manually choose the number of layers, the number of nodes in each layer and the transfer function for each layer. These are all critical decisions which affect the quality of the final network. Generally, the neural network predictions become more accurate as the number of hidden layers and/or neurons increases. However, if too complicated an architecture is used, "overfitting" will occur. As such, the network provides very accurate replication of the learning data set but poor performance predicting values between learning set points. In such cases, neural networks have poor generalization capability to any values outside the training data. This problem can be avoided by limiting the number of hidden layers and hidden nodes. Although a back-propagation network must have at least one hidden layer, 80% of all problems can be solved with a single layer. The most complex problem can be solved with three hidden layers.

All the geological and socio-demographic variables were used as neuron nodes in input lay, and death rate was used as target variable in output layer. Note that six dummy variables (six nodes) were used to quantify seven-category geomorphology, but the earthquake intensity was used as an ordinal variable (one node). Therefore, there are 13 input nodes and 1 output nodes in the neural network.

The next key step is to construct an optimal neural network to learn the associations between the geological and socio-demographic factors and child mortality. To have an optimum model, sensitivity analyses were performed to determine number of hidden layers and nodes. Observations and findings are given as follows:

(1) *Number of hidden layers*. By keeping the number of nodes to 10 while varying the number of hidden layers from 1–5, it was found that the correlation coefficients for the training set increased to 0.80 as the number of hidden layers reached 2 and then decrease to 0.69 as it reached 5. Similarly, the correlation coefficients for the testing set increased to 0.65 as the number of hidden layer reached 2 and then decreased to 0.55 as it reached 5. It was also found that the RMS errors decreased as the number of hidden layers increased from 1–2, and then increased from 2–5. In addition, the training time increases as the number of hidden layers increases from 2–5, which makes the ANN inefficient. Thus, 2 hidden layers were selected for efficiency and accuracy.

(2) *Number of nodes in hidden layer*. Firstly, by increasing the number of nodes from 1–10 in the first hidden layer holding 1 node in the second, it was found that for the training set the correlation coefficient increased from 0.63–0.86 as number of nodes reached 6 and then decreased to 0.65 as it reached 10; for the testing set the correlation coefficient increased from 0.59–0.70 and then decreased to 0.60. Hence, 6 nodes were selected in the first hidden layer. Secondly, by increasing the number of nodes from 1–10 in second hidden layer holding 6 nodes in the first, it was found that the correlation coefficient decreased from 0.86–0.65 for the training set and from 0.70–0.58 for the test set. Hence, 1 node was selected in second hidden layer.

In short, a network was selected in which there were to hidden layers with 6 nodes in the first hidden layer and 1 in the second. The network is a hybrid network with sigmoid transfer functions in the first hidden layer and the output node and Gaussian transfer functions in the second hidden layer. Qnet2000 by Vista Services, Inc. was used for neural network construction and performance evaluation.