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ORIGINAL PAPER

The danger of mapping risk from multiple natural hazards

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Abstract In recent decades, society has been greatly affected by natural disasters (e.g. floods, droughts, earthquakes), and losses and effects caused by these disasters have been increasing. Conventionally, risk assessment focuses on individual hazards, but the importance of addressing multiple hazards is now recognised. Two approaches exist to assess risk from multiple hazards: the risk index (addressing hazards, and the exposure and vulnerability of people or property at risk) and the mathematical statistics method (which integrates observations of past losses attributed to each hazard type). These approaches have not previously been compared. Our application of both to China clearly illustrates their inconsistency. For example, from 31 Chinese provinces assessed for multi-hazard risk, Gansu and Sichuan provinces are at low risk of life loss with the risk index approach, but high risk using the mathematical statistics approach. Similarly, Tibet is identified as being at almost the highest risk of economic loss using the risk index, but lowest risk under the mathematical statistics approach. Such inconsistency should be recognised if risk is to be managed effectively, whilst the practice of multi-hazard risk assessment needs to incorporate the relative advantages of both approaches.

Keywords Multi-hazard risk assessment · Risk index · Mathematical statistics · Economic loss · Human life loss

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1 Introduction

The impacts of one hazardous event are often exacerbated by interaction with another (Marzocchi et al. 2009). The mechanism by which these interactions occur varies and may be a product of one event triggering another, or 'crowding', where events occur independently without evident common cause, but in close proximity, spatially, temporally or both (Tarvainen et al. 2006; Carpignano et al. 2009; Marzocchi et al. 2012). The 2011 Tohoku earthquake which led to a tsunami and subsequently the Fukushima Daiichi nuclear disaster (Norio et al. 2011) is an event cascade and an example of triggering, whilst flooding in China's Yangtze River Delta arising from a typhoon occurring at the same time as annual monsoonal rainfall is an example of event crowding (Liu et al. 2013). Close proximity between events may lower resilience to disaster and make recovery more difficult and illustrates how risk from multiple natural hazards is often greater than that suggested by risk assessment that considers hazards as independent events.

Multi-hazard risk assessment (MHRA) has been developed to combat the limitations of single-hazard appraisal (Armonia Project 2006; Marzocchi et al. 2009; Di Mauro et al. 2006), with MHRA approaches building on the methods developed for single-hazard risk assessment, but additionally considering hazard interaction. The aim is to develop a more complete understanding of risk by assessing, and usually mapping, either the relative danger or expected losses (social, economic, environmental) due to the occurrence of multiple natural hazards in an area(Armonia Project 2006; Dilley et al. 2005). Two MHRA approaches exist, one developing a risk index, and the other using a mathematical statistics approach. There are no MHRA studies that compare analysis of risk using these two approaches for the same area. Therefore, this paper compares the risk index and mathematical statistics methods (definition and methodology) and then applies them to China's provinces to analyse differences, including data needs and results. After discussing possible reasons for differences in results, the relative merits of these two methods are summarised.

2 Methodology

2.1 The risk index approach

The risk index approach addresses the factors that lead to a disaster (disaster formation). Risk is defined as the probability of loss caused by the interactions between the vulnerability, exposure and the hazard. Risk is most commonly expressed as in Eq. (1) (ISDR 2004):

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \times \text{Exposure} \tag{1}$$

Where hazard is the presence of potentially damaging physical events in an area, exposure is the number, types and monetary value of elements that are exposed to that hazard, and vulnerability refers to intrinsic characteristics of those elements that make them more or less susceptible to adverse impact. Selection of component indicators for hazard, vulnerability and exposure, and calculation of associated weights are key steps. The process is an extension of that used for an individual hazard, with risks from individual hazards aggregated in a unified MHRA index. Aggregation may proceed in two ways. The first is to address hazard, vulnerability and exposure for individual hazards and then sum for the multi-hazard risk index (Granger and Trevor 2000; Munich Reinsurance Company 2003;

Khatsu and van Westen 2005; Schmidt-Thomé 2006; Thierry et al. 2008; Kunz and Hurni 2008; SCEMDOAG 2009):

$$R = f\left(\sum_{i=1}^{n} H_i, \sum_{i=1}^{n} Vi, \sum_{i=1}^{n} Ei\right) \tag{2}$$

An alternative aggregation approach is used in which each hazard risk index is first assessed individually for a given area. Weights (see below) are then assigned to each individual hazard risk and summation used to derive the multi-hazard risk index (Bell and Glade 2004; UNDP 2004; Lavalle et al. 2005; Dilley et al. 2005; Wipulanusat et al. 2009; Shi 2011):

$$R = \sum_{i=1}^{n} f(Hi, Vi, Ei) \tag{3}$$

In both cases, R is multi-hazard risk, H_i is hazard, V_i is vulnerability, E_i is exposure, and i represents each individual hazard.

However, most methods in both aggregation approaches [Eqs. (2) and (3)] suffer the drawback that the multi-hazard risk index is calculated by aggregating all single-hazard risks with equal weight (Table 1), which does not adequately reflect the varied impacts of different hazards present in the same area. Whilst both aggregation methods have advanced MHRA and can be used to better compare the relative degree of danger between different areas, these applications utilise hazard, vulnerability and exposure to assess the final multi-hazard risk without a consideration of probabilities and exceedance probabilities (the probability that a specified level of loss, or a greater loss, will occur), and thus, these approaches cannot reflect the real risk in the study areas. Thus, the risk index is useful in a relative sense, but is less helpful in an absolute sense for determining total losses.

2.2 The mathematical statistics approach

The mathematical statistics approach is based upon the analysis of observed natural disasters. Risk is defined as a product of the probability of occurrence of a hazardous event and the consequences of such an event for exposures (the magnitude of impact resulting from realisation of the hazard). Risk is expressed as (IUGS 1997):

$$\text{Risk} = \text{Probability} \times \text{Consequence} \tag{4}$$

This is the basic model for the mathematical statistics method, and its associated loss curve is shown in Fig. 1. Loss (L) is the loss (damage) associated with the disaster, and EP(L) is the exceedance probability for the corresponding loss. Through application of this approach, an exceedance probability-loss curve can be built, which shows the likelihood of losses of different magnitudes, and which is used to estimate and evaluate risk of future disasters. Both parametric and nonparametric methods are used to estimate the required probabilities (FEMA 2004; Grünthal et al. 2006; Van Westen 2008; Schmidt et al. 2011; Linares-Rivas 2012; Frolova et al. 2012; Liu et al. 2013) (Table 1).

The mathematical theory in the parametric method assumes that disaster losses follow a known distribution function (curve). Historical loss data sets are often used to estimate the distribution function parameters that are then used to calculate the probability distribution. This methodology has been widely used in risk assessment. For instance, Grünthal et al.

Table 1 Multi-hazard risk assessment approaches and applications

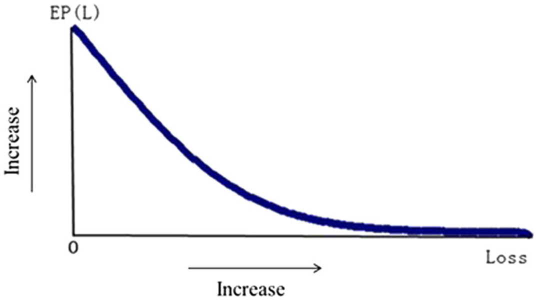
Country (or Institution)	Study area	Hazards	Remarks
A. The risk index approach			
Australia (AGSO—Australian Geological Survey Organisation) Granger and Trevor (2000)	Mackay (Australia)	Cyclone (flood, strong wind, storm tide)	Equation (2). Multi- hazard risk was calculated by combining the highest rank for the individual hazards and overall community vulnerability
Munich Reinsurance Company (2003)	Global	Earthquake, windstorm, flood, volcanic eruption, bush fire, frost	Equation (2). Historical loss data were used to decide the weight for each single hazard
German Bell and Glade (2004)	Bíldudalur (NW-Iceland)	Snow avalanche, debris flow, rock fall	Equation (3). Multi-hazard risk map was created by overlaying single-hazard risk maps with equal weight
United Nations Development Programme (UNDP 2004)	Global	Earthquake, tropical cyclone, flood, drought	Equation (3). Multi-hazard risk index was calculated by aggregating single-hazard risk index
Europe (Joint Research Centre) Lavalle et al. (2005)	Europe	Flood, forest fire, drought, heat wave	Equation (3). Multi-hazard risk index was calculated by aggregating single-hazard risk index
World Bank Dilley et al. (2005)	Global	Earthquake, cyclone, flood, landslide, drought, volcanic hazards	Equation (3). Multi-hazard risk index was calculated by aggregating single-hazard risk index
India Khatsu and van Westen (2005)	Kohima Town (India)	Earthquake, landslide, fire	Equation (2). Multi-hazard map was created by overlaying single-hazard map
Europe (European Spatial Planning and Observation Network) Schmidt-Thomé (2006)	The enlarged European Union (EU-29)	Avalanche, drought, earthquake, extreme temperature, flood, forest fire, landslide, storm surge, tsunami, volcanic eruption, winter and tropical storm, technological hazards	Equation (2). The Delphi method was used to assign weight to each single hazard
Cameroon Thierry et al. (2008)	Mount Cameroon	Volcanic hazards, landslide, earthquake	Equation (2). Geographic information system (GIS) was used to combine each single hazard and element at risk
Switzerland Kunz and Hurni (2008)	Switzerland	Flood, mass movements, snow avalanche	Equation (2). Multi-hazard map was created by overlaying single-hazard map

Table 1 continued

Country (or Institution)	Study area	Hazards	Remarks
The USA (SCEMDOAG 2009)	The USA	Coastal events, dam failure, drought, flood, fog, geophysical events, human-induced hazard events, severe thunderstorm events, temperature extreme, wildfire, winter weather	Equation (2). The multi-hazard index was constructed by summing the frequency of occurrence for each hazard with equal weight
Thailand Wipulanusat et al. (2009)	Pak Phanang basin (Thailand)	Drought, flood	Equation (3). Multi-hazard risk map was created by overlaying single-hazard risk map
China Shi (2011)	China	Earthquake, typhoon, flood, drought, landslide and debris flow, sandstorm, snow, hail, storm surge, frost, forest fire, grassland fire	Equation (3). The frequency of occurrence for each hazard was used to decide the weight
B. The mathematical statistics approach			
The US FEMA (2004)	The USA	Flood, hurricane, earthquake	Parametric method and historical information were used to produce loss estimates
German Grünthal et al. (2006)	Cologne (German)	Storm, flood, earthquake	Parametric method
The Netherlands Van Westen (2008)	Tegucigalpa (Honduras)	Landslide, flood, earthquake, technological hazards	Historical information and parametric method were used to estimate annual loss
New Zealand Schmidt et al. (2011)	Hawke's Bay (New Zealand)	Earthquake, storm, flood	Synthetic loss curves were developed by a combination of nonparametric and parametric method
Central American Probabilistic Risk Assessment Program Linares-Rivas (2012)	Latin America and the Caribbean Region	Earthquake, hurricane, volcanic hazards, flood, tsunami, landslide	Historical information and parametric method were used to estimate annual loss for several return periods
Russia Frolova et al. (2012)	Russian Federation	Earthquake, landslide, mud flow, flood, storm, avalanche	Parametric method was used to estimate loss
China Liu et al. (2013)	Yangtze River Delta (China)	Flood, typhoon	Nonparametric method was used to calculate possible loss in different multi-hazard return periods

(2006) calculated exceedance probability–mean wind speed curves for windstorm risk assessment using Schmidt and Gumbel distributions (Gumbel 1958). Stedinger et al. (1992) estimated distribution function parameters by the method of moments for Gumbel type, Pearson type III, Weibull and lognormal curves; instead, Grünthal et al. (2006) used these distributions to build exceedance probability–discharge curves for flood risk assessment.

Fig. 1 Exceedance probability-loss curve



There is sometimes a lack of historical observations, so it can be difficult to develop a probability distribution function that reflects the real situation for parameter estimation. In these circumstances, a nonparametric method is used, which may employ histogram density estimation, kernel density estimation or information diffusion to derive probability estimates. Histogram density estimation is easy to use, but the results obtained are crude and are greatly influenced by the interval choice. Kernel density estimation (Rosenblatt 1956; Parzen 1962) are closely related to histograms, but can be endowed with properties such as smoothness or continuity by using a suitable kernel. However, the key problem of how to choose an appropriate smoothing parameter still remains. The information diffusion method was introduced by Huang (1997) to overcome this problem and improves the accuracy of natural disaster risk assessment. The information diffusion method can use sample data to assess natural disaster risk, and Huang (2000) showed it to be about 28 % more efficient than histogram density estimation.

These two risk assessment approaches are distinct, in that the risk index method primarily serves to aid understanding of the disaster formation mechanism, as it strives for an appreciation of the relative importance of hazard, vulnerability and exposure (of human and physical systems) and the interaction between these elements, in the overall determination of risk (Shi 1996; Wisner et al. 2004). Conversely, the statistics method expresses risk as probabilistic loss and is useful in estimating and evaluating losses from potential future disaster. It gives more consideration to the probability of occurrence, but relative to the risk index approach, exposure and vulnerability are neglected.

3 Application to China

3.1 Data

These approaches have not previously been compared, whilst researchers rarely explicitly justify their chosen approach. Their comparison is important to develop more transparent MHRA that would better inform management of risk from multiple hazards. We therefore compared the two MHRA approaches via their application to a common area that experiences significant natural hazards. A history of natural disasters driven by different natural hazards, plus a growing population and economy at risk, makes China a suitable region to conduct this comparison (Wang et al. 2008). For both approaches, nine natural hazards including flood, drought, heat wave, cold wave, earthquake, landslide, storm (typhoon and local storm), wildfire and avalanche were addressed to calculate the risk to human life and economic production.

Table 2 Data for multi-hazard risk assessment in China

Approach	Data	Index	Time interval	Source
Risk index approach	Socio-economic data	GDP, population size, gender ratio, age structure, traffic condition, telecommunication facilities, medical condition	2013	China statistical yearbook
	Historical disaster data	Number of disaster	1981–2012	EM-DAT, the OFDA/CRED international disaster database (http://www.em-dat.be)
		Deaths and economic loss caused by disaster	1981–2012	
Mathematical statistics approach	Socio-economic data	GDP, population size	1981–2012	China statistical yearbook
	Historical disaster data	Deaths and economic loss caused by disaster	1981–2012	EM-DAT, the OFDA/CRED international disaster database (http://www.em-dat.be)

Historical data on natural disasters in China were drawn from the EM-DAT International Disaster Database for 1981–2012 and used in application of both approaches. The approaches differ in their requirements for socio-economic data, in terms of both data type and time series, which reflects differences in the complexity of the approaches. The risk index requires socio-economic data for multiple variables, but only 1 year of data is required (Table 2). The mathematical statistics approach is less demanding in terms of the variety of socio-economic data required, but a longer time series is needed (Table 2).

3.2 Application and results

The risk index approach was applied such that the multi-hazard index was the sum of each hazard value multiplied by its weight, calculated according to the average historical death toll associated with this hazard (Munich Reinsurance Company 2003). The normalised multi-hazard index to human life is shown in Fig. 2a. Provinces with a high multi-hazard index value were mainly located in south-eastern China. Population age structure, gender ratio and quality of supporting infrastructure (transport routes, telecommunication facilities and medical facilities) were used as indicators to calculate the vulnerability index (Cutter et al. 2003; Villagran de Leon 2006; SCEMDOAG 2009) to human life using the entropy weight method[1] (Zou et al. 2006; Miao and Ding 2015). As shown in Fig. 2b, Provinces with a high vulnerability index value were mainly located in western China. The exposure index to human life loss was represented by population density. As shown in Fig. 2c, Shanghai has the highest exposure index. The multi-hazard risk index to human life was then calculated by aggregating the multi-hazard index, the vulnerability index and the exposure index with equal weight (Fig. 2d). This methodology was used in assessing

[1] Entropy measures the amount of useful information in the indicator provided. When the difference in one indicator between different assessment units is small, the entropy is great; it illustrates that this indicator provides less useful information, and the weight of this indicator should be set correspondingly small. On the other hand, if the difference is large and the entropy is small, the weight would be big.

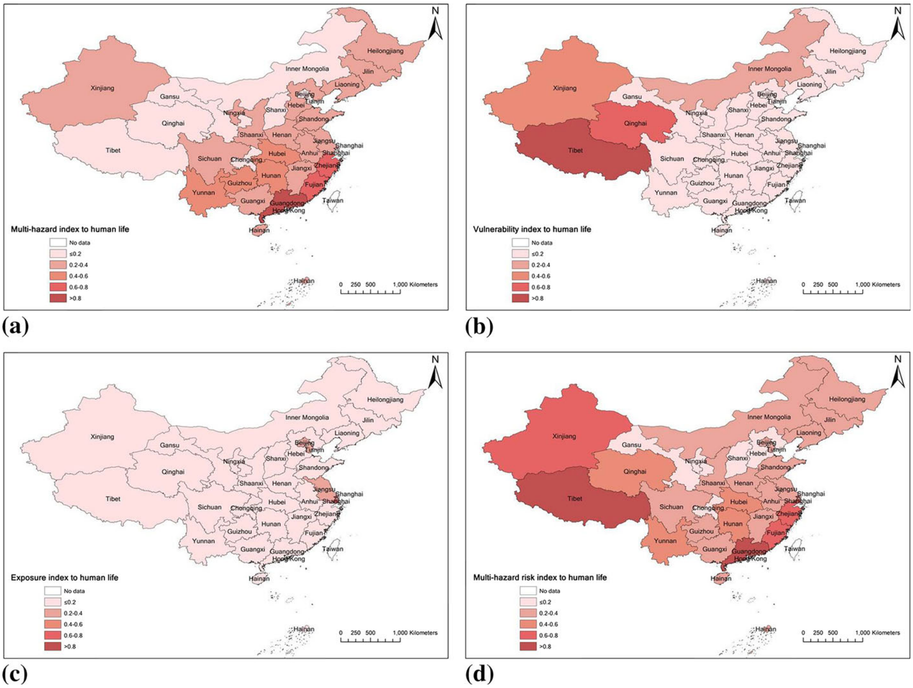


Fig. 2 Multi-hazard risk assessment to human life in China (2013) using the risk index approach (0 represents the lowest value, and 1 represents the highest value). **a** Multi-hazard index to human life. **b** Vulnerability index to human life. **c** Exposure index to human life. **d** Multi-hazard risk index to human life

economic loss, with GDP per km^2 as the exposure index. The hazard index, vulnerability index, exposure index and multi-hazard risk index to economic loss are shown in Fig. 3.

The information diffusion method (Huang 1997) was adopted in the mathematical statistics approach. The exceedance probability (EP) distribution of multi-hazard loss was calculated based on observed disaster loss data (1981–2012), and an EP loss curve developed. Multi-hazard risk to life and GDP was mapped for 10-, 20- and 50-year hazard return periods (Figs. 4, 5). Estimated losses are expressed as deaths per million people and ratio of economic loss to production, so population size and GDP in 2013 were used to probabilistically estimate deaths and economic loss in 2013 attributed to multi-hazard with a 20-year return period (Fig. 6).

4 Comparative performance

Comparing these with the risk maps generated using the risk index approach and mathematical statistics approach shows that the results are inconsistent (Figs. 2d, 3d, 6a, b). For instance, Gansu and Sichuan provinces are at low risk of life loss with the risk index approach (Fig. 2d), but high risk using the mathematical statistics approach (Fig. 6a). Similarly, Tibet is identified as being at almost the highest risk of economic loss using the risk index (Fig. 3d), but lowest risk under the mathematical statistics approach (Fig. 6b).

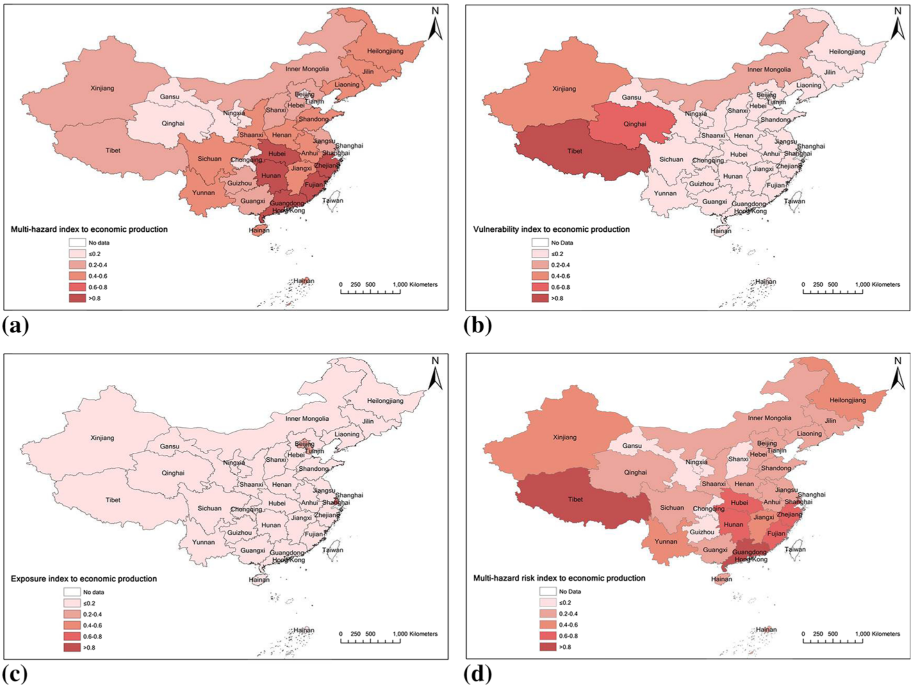


Fig. 3 Multi-hazard risk assessment to loss of economic production (GDP) in China (2013) using the risk index approach (0 represents the lowest value, and 1 represents the highest value). **a** Multi-hazard index to economic production. **b** Vulnerability index to economic production. **c** Exposure index to economic production. **d** Multi-hazard risk index to economic production

The risk index expresses risk using a synthetic unitless indicator, whilst the mathematical statistics approach expresses risk as integrated losses (lives, GDP); hence, results cannot be compared directly. However, Spearman rank correlation (Spearman 1904) coefficients of 0.17 and 0.33 for multi-hazard risk to human life and loss of economic production clearly reveal the lack of consistency between the two approaches, which supposedly both assess the same multi-hazard risk. This is further illustrated by Table 3, the risk ranking for the two approaches.

There are several possible explanations for this observation. Firstly, the risk index and mathematical statistics approaches adopt different assessing elements. The risk index approach assesses risk from component indicators for hazard, vulnerability and exposure, but mathematical statistics approach adopt probability and corresponding loss to measure the risk. Second, MHRA using the risk index approach draws on vulnerability and exposure data for a single year only (2013 in our analysis), whereas the mathematical statistics method makes a probabilistic assessment that must draw on a long run time series of observed losses (32 years in our case). Thirdly, and related to this, is that the mathematical statistics approach does not explicitly address changes in vulnerability (of population and property), but these values change from year to year as a country develops. A region experiencing rapid population growth may see a major change in the population that is vulnerable to natural hazards, but the risk index reflects this vulnerability for 1 year only (most likely that for which the latest data are available), and hence is unlikely to be

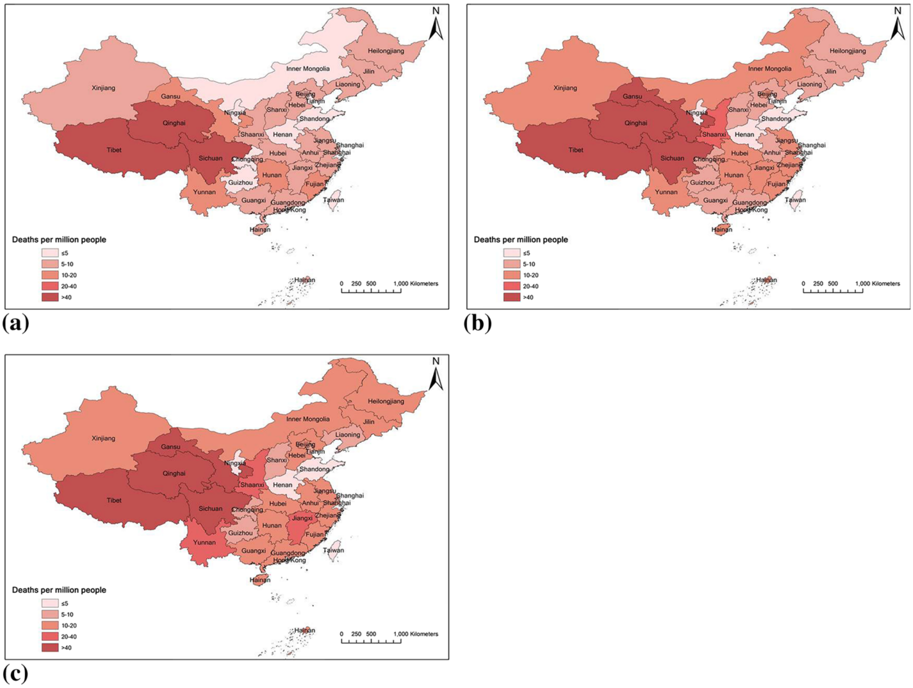


Fig. 4 Multi-hazard risk to human life for selected event return periods. **a** 10-year return periods. **b** 20-year return periods. **c** 50-year return periods

representative of vulnerability over the long run. The mathematical statistics approach does not address vulnerability directly, but does so indirectly, via observed losses, which in contrast are for the long run. Fourthly, the risk index is also similarly sensitive to changes in population (or property) exposure (e.g. the population density of Shanghai, at 3809 people per km^2 is 1494 times higher than that of Tibet). Finally, the mathematical statistics approach underestimates the influence of extreme events whose return periods are substantially longer than the time period of the observed loss data. This is evident in the case of Sichuan which is calculated as high risk (to human life) in the 20-year return period, because this region experienced an earthquake in 2008 whose magnitude (and death toll, a reported 87,587 deaths) (USGS 2012) had a return period that was much longer than that of the observed loss record. If more extreme natural hazard events are included, the observed loss data would increase exceedance probabilities and the resulting multi-hazard risk estimation.

Despite the difference in results, it cannot be concluded that one approach is wrong or that neither is correct. These two approaches both provide a measure of risk, but they each have a different emphasis. Both approaches have certain advantages and drawbacks which reflect that one emphasises the disaster formation mechanism (and is best used to assess relative risk), and the other emphasises the expected losses (thus reflecting real-world observations, but neglecting exposure and vulnerability) (Table 4). Our analysis for China has demonstrated that these two approaches can differ in the estimation of risk, so much so that a complete reversal of the risk picture gained is possible if switching from one approach to the other. This has significant implications for management of that risk.

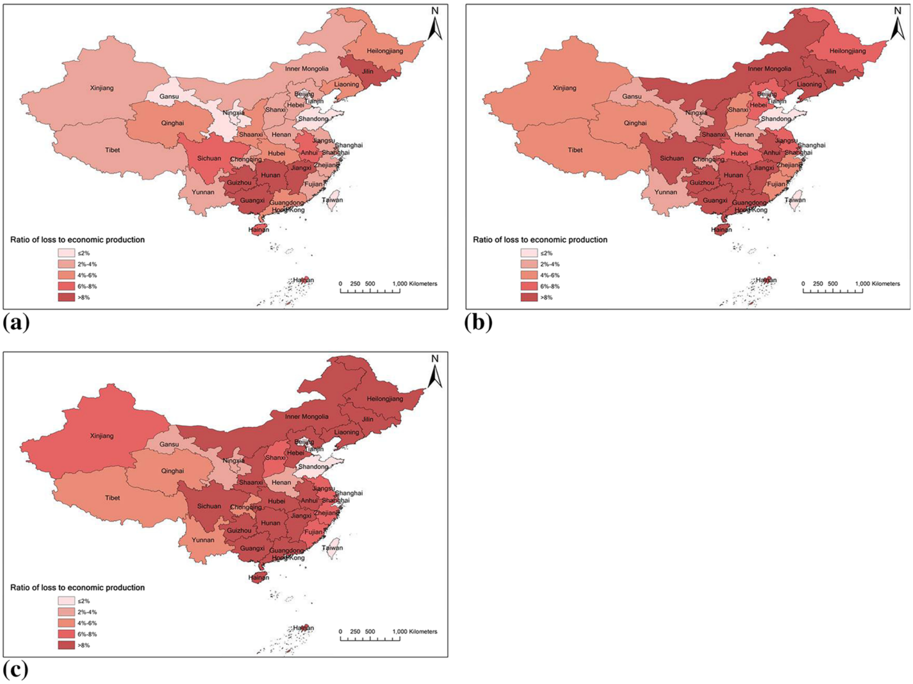


Fig. 5 Multi-hazard risk to economic production for selected event return periods. **a** 10-year return periods. **b** 20-year return periods. **c** 50-year return periods

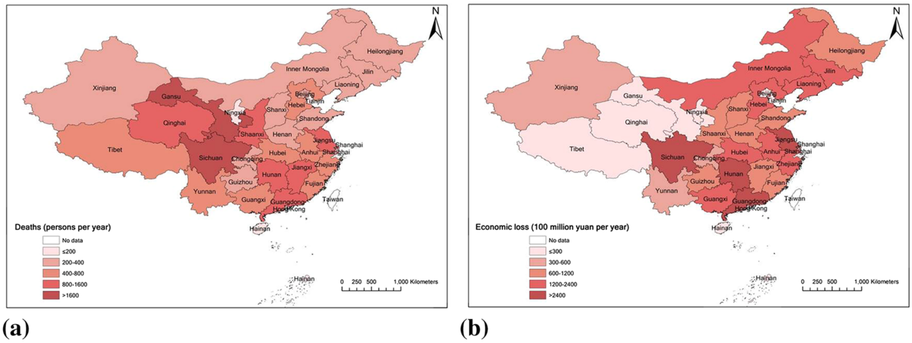


Fig. 6 Death and economic loss in 2013 to multi-hazard with a 20-year return period. **a** Deaths in 2013 to multi-hazard with a 20-year return period. **b** Economic loss in 2013 to multi-hazard with a 20-year return period

5 Conclusion and discussion

We conclude that in assessing risk from multiple natural hazards, there is a need to recognise that the results of a MHRA are heavily dependent upon the approach adopted, and that there is clearly danger to effective risk management, in unwittingly choosing one

Table 3 Province ranking by the risk index and mathematical statistics approaches to human life and economic production

Province	Risk ranking to human life		Risk ranking to economic production	
	Risk index	Mathematical statistics	Risk index	Mathematical statistics
Beijing	25	26	16	29
Tianjin	18	30	24	26
Hebei	27	10	26	6
Shanxi	30	20	28	21
Inner Mongolia	14	24	14	10
Liaoning	22	17	13	3
Jilin	23	23	20	14
Heilongjiang	16	18	9	16
Shanghai	1	27	1	13
Jiangsu	13	8	12	2
Zhejiang	6	13	6	9
Anhui	11	14	17	8
Fujian	5	11	5	17
Jiangxi	26	6	11	11
Shandong	17	21	18	20
Henan	24	22	22	18
Hubei	8	12	7	7
Hunan	10	4	4	5
Guangdong	2	5	3	1
Guangxi	15	16	21	12
Hainan	19	29	23	25
Chongqing	29	25	30	22
Sichuan	21	1	19	4
Guizhou	12	28	27	19
Yunnan	9	9	10	23
Tibet	3	15	2	31
Shaanxi	20	7	25	15
Gansu	31	2	29	27
Qinghai	7	3	15	28
Ningxia	28	31	31	30
Xinjiang	4	19	8	24

approach over another, with for example, choice of approach driven by practical considerations, such as data availability.

Comparative analysis of multi-hazard risk merits further work, for different territories and geographic scales, to verify our findings. However, the degree of inconsistency between the approaches revealed by our analysis implies that risk assessors must recognise the relative merits of their adopted approach, and clearly explain to those with natural hazard risk management responsibilities (including politicians, policy makers and

Table 4 Relative merits of multi-hazard risk assessment approaches

	Risk index	Mathematical statistics
Advantages	Considers the disaster formation mechanism	Calculates the possible loss
	Helps to understand the contribution of hazard, vulnerability and exposure to overall risk	Calculates exceedance probability for risk
	Better compares the relative danger between different areas	
	Simple to operate	
Disadvantages	Cannot calculate probability of the risk	Neglects vulnerability and exposure
	Weight problem is not resolved	Potentially biased by extreme events
	Neglects interaction between different hazards	Data update is complex
		Neglects interaction between different hazards

planners) which approach has been used and why. As shown in Fig. 7, the approach adopted will likely depend upon the objective of the MHRA. Loss assessors (e.g. the insurance industry) may favour the mathematical statistics approach, but those seeking to proactively manage multi-hazard risk require a deeper understanding of the factors that underpin that risk and so will favour the risk index approach. The evident disparity between these two approaches means that effective management of multi-hazard risk, which better protects life and property, may be constrained.

A hybrid MHRA approach that integrates the best of the index and statistical approaches is clearly worth pursuing. This could be achieved by analysing risk considering the disaster formation mechanism considering hazard, vulnerability and exposure, and calculating possible loss and corresponding probability of loss under different natural hazard scenarios.

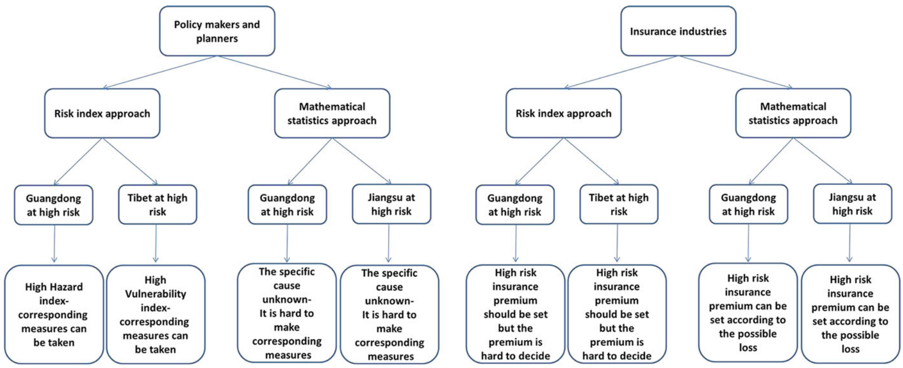


Fig. 7 Multi-hazard risk assessment (economic loss) for relevant stakeholders (**a**) policy makers and planners, and (**b**) insurance industries

A key element here would be consideration of the interaction between hazards, the interaction of hazards and vulnerability, and the frequency of hazard occurrence.

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