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# The danger of mapping risk from multiple natural hazards

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# The danger of mapping risk from multiple natural hazards

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**Abstract**

Climate change is increasing the frequency of natural hazards such as intense storms, flood and landslide. Conventionally, risk assessment focuses on individual hazards, but the importance of addressing hazards collectively 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 (to loss of economic production), Tibet ranks second according to the risk index approach, but last using the mathematical statistics approach. Such inconsistency should be recognised if risk from climate change is to be managed effectively, whilst the practice of multi-hazard risk assessment needs to incorporate the relative advantages of both approaches.

Key words: Multi-hazard risk assessment; Risk index; Mathematical statistics; Losses in economic production and human life; China

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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 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 those 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 to analyze differences, including data needs and results. After discussing possible reasons for differences in results, the relative merits of these two methods are summarized.

## 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 arising from interaction between the vulnerability of receptors (such as people, infrastructure, crops, the environment), and their exposure to hazards. Risk is most commonly expressed as in equation (1) (ISDR, 2004):

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability} \quad (1)$$

Where hazard is the presence of potentially damaging physical events in an area, exposure is a characterisation of receptors exposed to that hazard, and vulnerability refers to intrinsic characteristics of those receptors 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 (See Table 1). 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:

$$R = f(\sum_{i=1}^{n} H_i,\ \sum_{i=1}^{n} V_i,\ \sum_{i=1}^{n} E_i) \qquad (2)$$

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:

$$R = \sum_{i=1}^{n} f(H_i,\ V_i\ , E_i) \qquad (3)$$

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 (equations (2) and (3)) suffer the drawback that the multi-hazard risk index is calculated by aggregating all single hazard risks with equal weight, 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, 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 with risk a product of the probability of occurrence of a hazardous event and the consequences of such an event for receptors (the magnitude of impact resulting from realization of the hazard). Risk is expressed as (IUGS, 1997):

$$\text{Risk} = \text{Probability} \times \text{Consequence} \quad (4)$$

This is the basic model for the mathematical statistics method and its associated loss curve is shown in Figure 1. Loss (L) is the loss (damage) associated with the disaster, and EP(L) is the exceedance probability for the corresponding loss (the probability that a specified level of loss, or a greater loss, will occur). 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 (See Table 1).

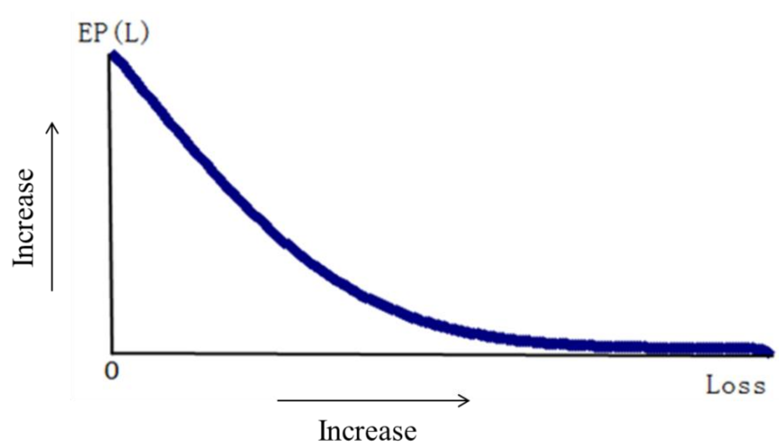



**Figure 1. Exceedance probability-loss curve**

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

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 first draws a histogram and curve according to varying degrees of disaster, then based on the curve type, adopts a moving average (using exponential smoothing or other methods) to analyse historical loss data. A mathematical statistics model can then be built to reflect the functional relationship between disaster degree and frequency. However, the results obtained with this method are crude and are greatly influenced by the interval choice. In order to overcome the disadvantages of histogram density estimation, Rosenblatt (1956) and Parzen (1962) proposed the use of kernel density estimation, which can be used to estimate the probability density function of arbitrary shapes. Kernel density estimates 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.

**Table 1. Multi-hazard risk assessment approaches and applications**

| | **A. The Risk Index Approach** | | |
|---|---|---|---|
| **Country (or Institution)** | **Study area** | **Hazards** | **Remarks** |
| Australia (AGSO-Australian Geological Survey Organisation) (Granger and Trevor, 2000) | Mackay (Australia) | Cyclone (flood, strong wind, storm tide). | Equation (2). Multi- hazard risk is calculated by the highest rank for the individual hazards (flood, strong wind, storm tide) and overall community vulnerability. |
| Munich Reinsurance Company (2003) | Global | Earthquake, windstorm, flood, volcanic eruption, bush fire, frost. | Equation (2). Historical loss data was 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 maps are combined single hazard risk maps with equal weight. |
| United Nations Development Programme (2004) | Global | Earthquake, tropical cyclone, flood, drought. | Equation (3). Multi-hazard risk index was calculated by summing all single hazard risks. |
| Europe (Joint Research Centre) (Lavalle et al., 2005) | Europe | Flood, forest fire, drought, heat wave. | Equation (3). Multi-hazard risk index is a sum of single hazard risks. |
| World Bank (Dilley et al., 2005) | Global | Earthquake, cyclone, flood, landslide, drought, volcanic hazards. | Equation (3). Multi-hazard risk index was calculated as the sum of the single-hazard risk index. |
| India (Khatsu and van Westen, 2005) | Kohima Town (India) | Earthquake, landslide, fire. | Equation (2). Multi-hazard was combined using an ArcGIS spatial query operation. |

| | | | |
|---|---|---|---|
| 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 different weights 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 was assessed by the overlay of the single hazard maps. |
| The United States (SCEMDOAG, 2009) | The United States | 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 the drought risk map with the flood 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**

| **Country (or Institution)** | **Study area** | **Hazards** | **Remarks** |
|---|---|---|---|
| The United States (FEMA, 2004) | The United States | Flood, hurricane, earthquake. | Hazus Multi-Hazard Software uses statistics and historical information to produces 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 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 events were considered to build hazard maps 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. |

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. Besides, as the probability of natural hazard occurrence is developed from historical observations the mathematical statistics approach likely underestimates multi-hazard risk as the frequency and return period of natural hazards alters with climate change.

# 3. Application to China

## 3.1 Data

These approaches have not previously been compared, whilst selection of approach chosen is rarely explicitly justified. Their comparison is important to developing more transparent MHRA that would better inform management of risk from climate change.

We therefore compared the two MHRA approaches via their application to a common area that experiences significant climate related 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.

Historical data on natural disasters in China was drawn from the EM-DAT International Disaster Database for 1981-2010, 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 one 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).

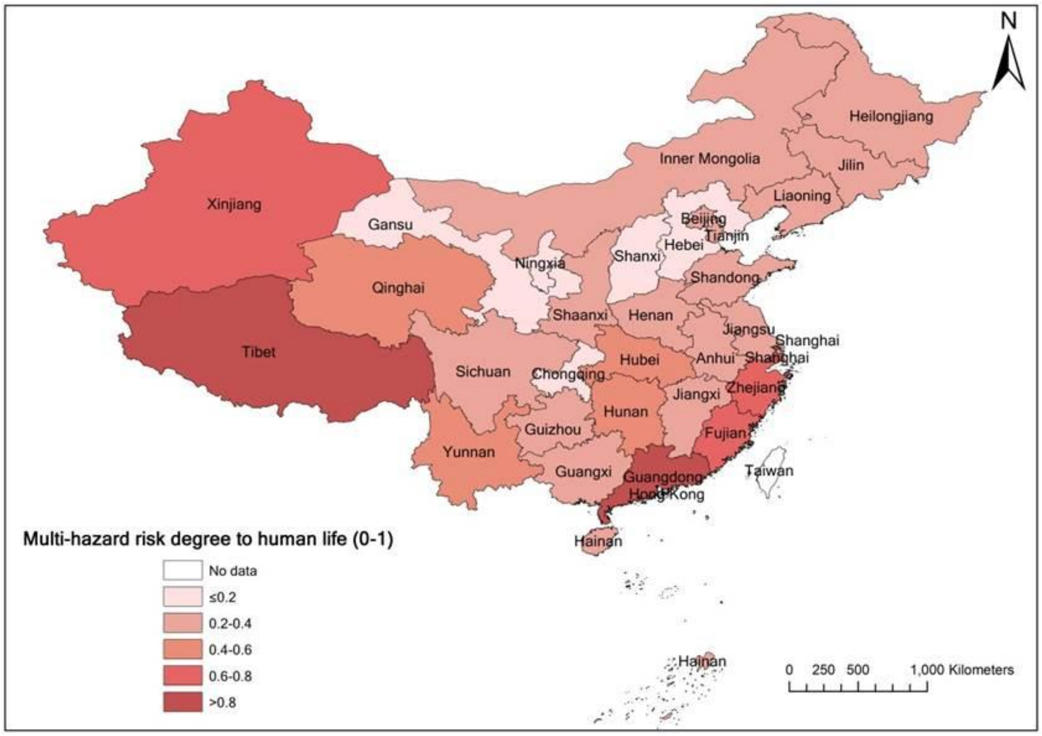
**Table 2. Data for multi-hazard risk assessment in the China**

| Method | Data | Index | Time interval | Source |
|---|---|---|---|---|
| Risk index method | Socioeconomic data | GDP, population size, gender ratio, age structure, traffic condition, telecommunication facilities, medical condition | 2011 | China Statistical Yearbook |
| | Historical disaster data | Number of disaster | 1981-2010 | EM-DAT, the OFDA/CRED international disaster database(http://www.em-dat.be) |
| | | Deaths and economic loss caused by disaster | 1981-2010 | |
| Mathematical statistics method | Socioeconomic data | GDP, population size | 1981-2010 | China Statistical Yearbook |
| | Historical disaster data | Deaths and economic loss caused by disaster | 1981-2010 | EM-DAT, the OFDA/CRED international disaster database(http://www.em-dat.be) |

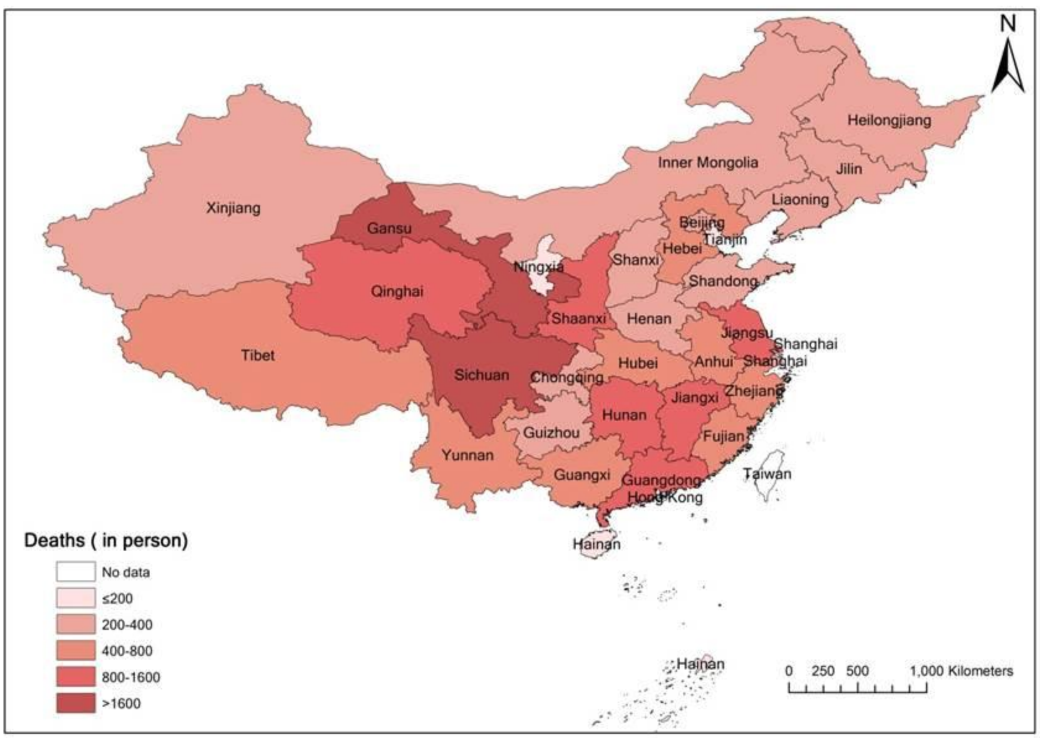
## 3.2 Application and results

The risk index approach was applied where 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). Population age structure, gender ratio, and quality of supporting infrastructure (transport routes, telecommunication facilities, and medical facilities) were used to calculate the vulnerability index (Villagran de Leon, 2006; SCEMDOAG, 2009) to human life using the entropy-weight method (Zou et al., 2006). The exposure index to human life loss was represented by population density. Multi-hazard risk index to human life was then calculated by aggregating the multi-hazard index, the vulnerability index and the exposure index (Figures 2a). This methodology was used in assessing economic loss, with GDP per $km^2$ as the exposure index (Figures 3a).

The information diffusion method (Huang, 1997) of curve parameter estimation was adopted in the mathematical statistics approach. The exceedance probability (EP) distribution of multi-hazard loss was calculated based on observed disaster loss data (1981-2010), and an EP loss curve developed. Multi-hazard risk to life and GDP was mapped for 10-, 20- and 50-year hazard return periods. Estimated losses are expressed as deaths per million people and ratio of economic loss to production, so population size and GDP in 2011 were used to probabilistically estimate deaths in 2011 attributed to multi-hazard with a 20-year return period (Figures 2b and 3b).

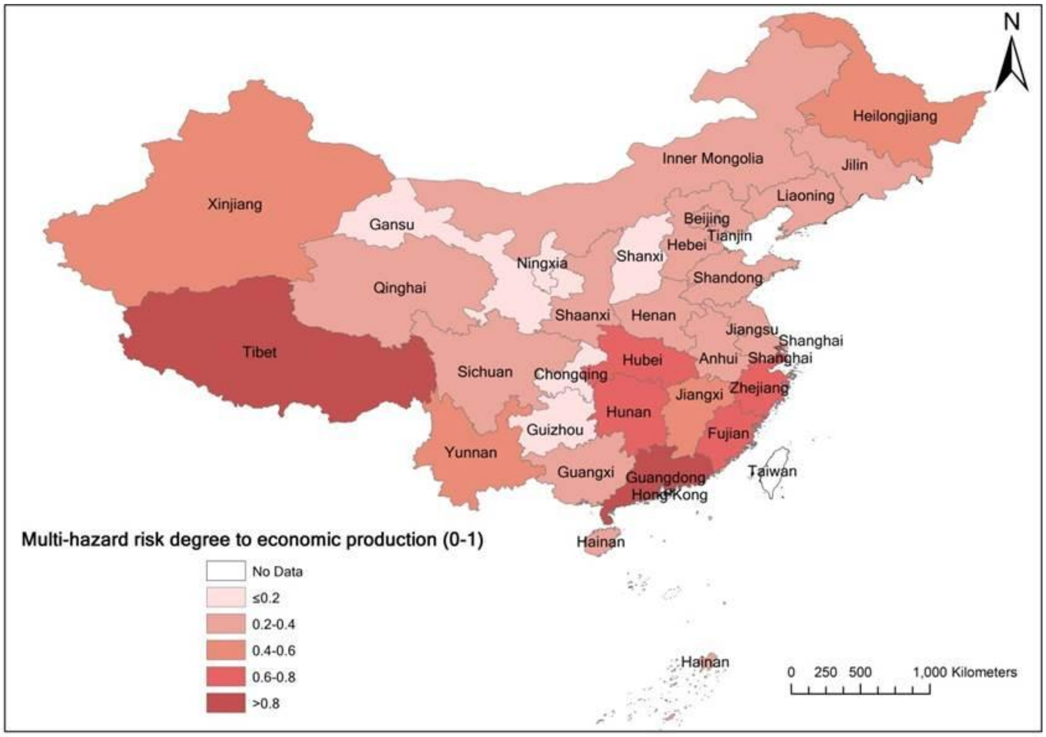



**a)** Risk index approach

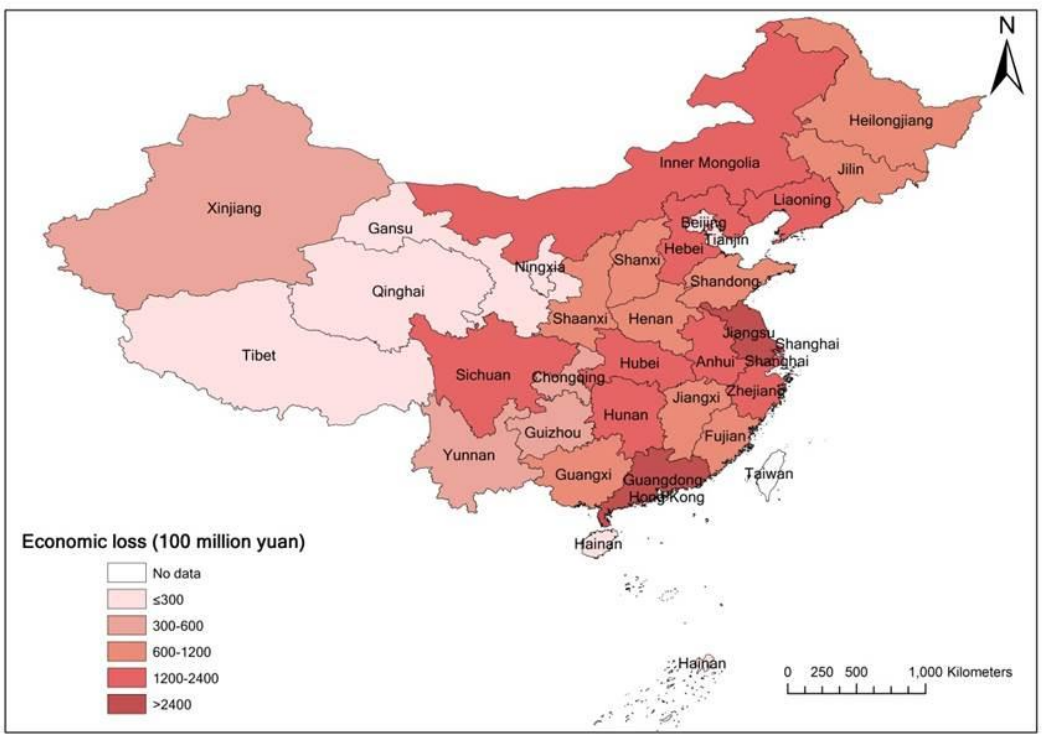



**b)** Mathematical statistics approach (20 years return period)

**Figure 2. Multi-hazard risk to human life in China (2011) using (a) the risk index approach (0 represents the lowest risk, and 1 represents the highest risk), and (b) the mathematical statistics approach with return period of 20 years**




**a)** Risk index approach



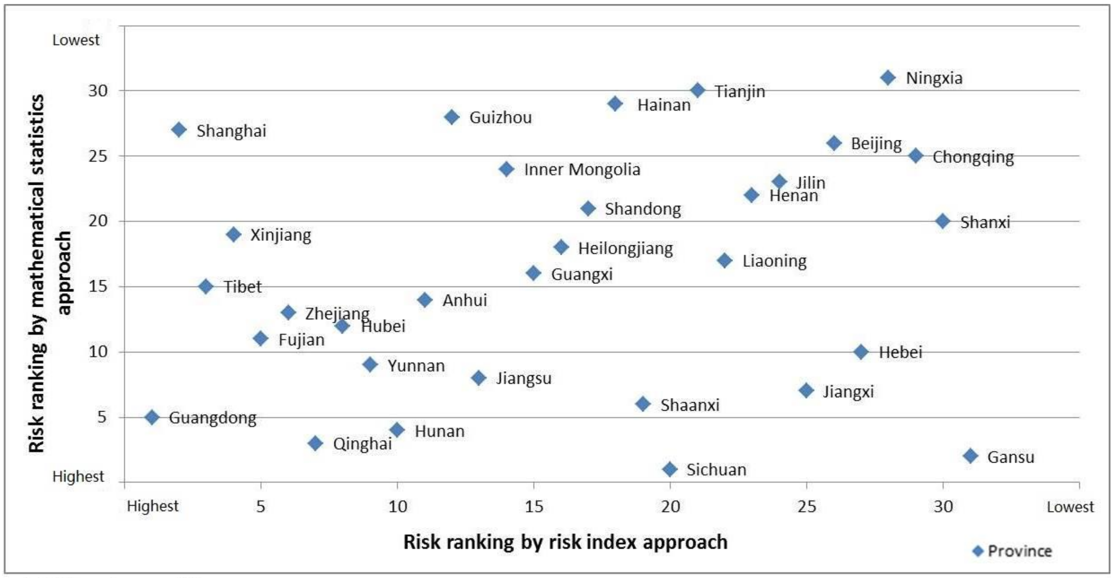

**b)** Mathematical statistics approach (20 years return period)

**Figure 3. Multi-hazard risk to loss of economic production (GDP) in China using (a) the risk index approach (0 represents the lowest risk, and 1 represents the highest risk), and (b) the mathematical statistics approach with return period of 20 years**

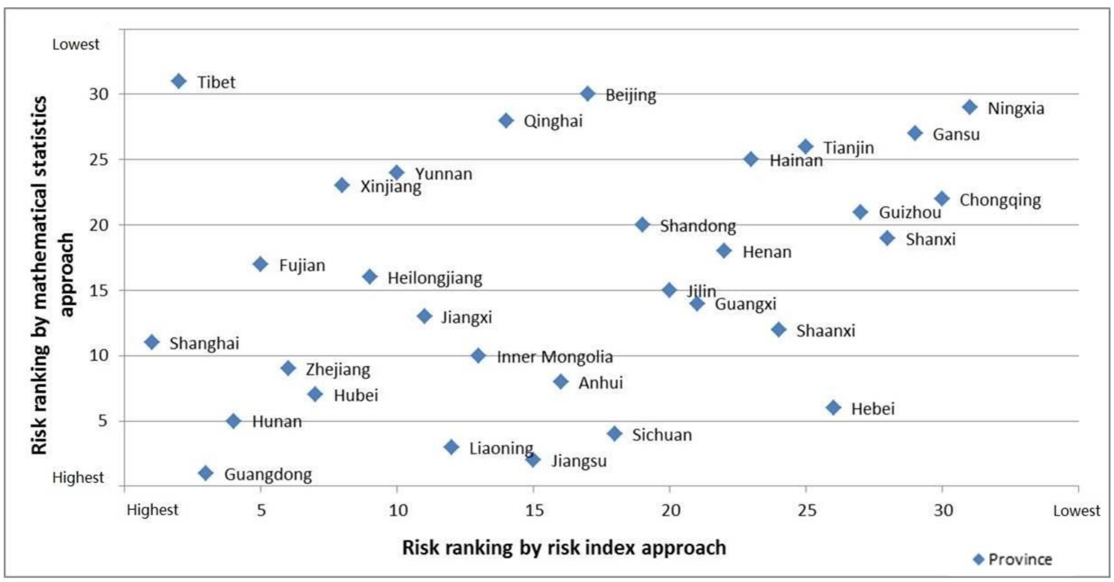
## 4. Comparative performance

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

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 0.21 and 0.34 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 Figure 4, a scatter plot of the risk ranking for the two approaches.




**a)** Risk to human life




**b)** Loss of economic production (GDP)

**Figure 4. Province ranking by the risk index and mathematical statistics approaches to (a) human life, and (b) economic production**

There are several possible explanations for this observation. Firstly, MHRA using the risk index approach draws on vulnerability and exposure data for a single year only (2011 in our analysis), whereas the mathematical statistics method makes a probabilistic assessment that must draw on a long run time-series of observed losses (30 years in our case). Second, 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 one year only (most likely that for which the latest data is available), and hence is unlikely to be 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. Thirdly, the risk index is also similarly sensitive to changes in population (or property) exposure (e.g. the population density of Shanghai, at 3,702 people per $km^2$ is 1,481 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 risk index analysis, 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, because they each have a different focus. Both approaches have certain advantages and drawbacks which reflect that one is focused on the disaster formation mechanism (and is best used to assess relative risk), and the other is focused on expected losses (thus reflecting real world observations, but neglecting exposure and vulnerability) (Table 3). 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.

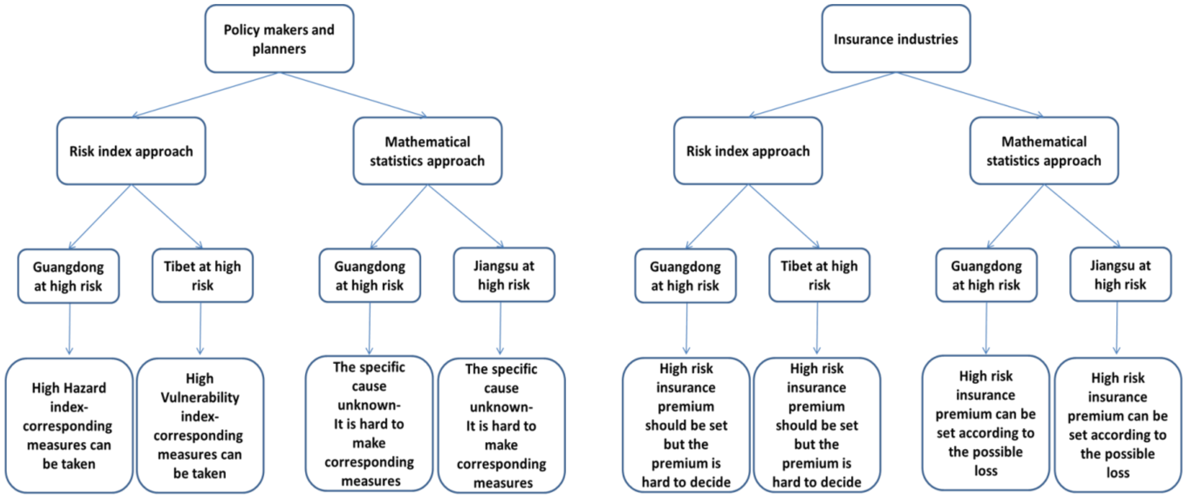
**Table 3. Relative merits of multi-hazard risk assessment approaches**

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

## 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 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 planners) which approach has been used and why. As shown in Figure.5, 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 pro-actively 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) Multi-hazard risk assessment for policy makers and planers    b) Multi-hazard risk assessment for insurance industries

**Figure 5. Multi-hazard risk assessment (economic loss) for relevant stakeholders (a) policy makers and planners, and (b) insurance industries**

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

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