An approach to assess an integrated risk caused by two hazards

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ABSTRACT: In this paper, we define an integrated probability risk of multi-hazards as the expected value of disaster, which is determined by a joint probability distribution and a disaster function. To overcome the difficulty of that, with a small sample, it is impossible to theoretically construct a valid distribution and a valid function; we develop the information diffusion technique to construct them. The 2-dimension normal diffusion and the 3-dimension normal diffusion are employed to construct a discrete joint probability distribution and a discrete disaster function, respectively.

KEYWORDS: integrated risk, multi-hazards, joint probability distribution, disaster function, information diffusion technique.

1 INTRODUCTION

In the latest United Nations' framework for disaster risk reduction 2015-2030 (UNISDR, 2015), international financial institutions, such as the World Bank and regional development banks, are proposed to consider the priorities for providing financial support and loans for *integrated disaster risk reduction*. The pursued goal is: prevent new and reduce existing disaster risk through the implementation of *integrated* and inclusive economic, structural, legal, social, health, cultural, educational, environmental, technological, political and institutional measures that prevent and reduce hazard exposure and vulnerability to disaster, increase preparedness for response and recovery, and thus strengthen resilience. The framework continues the idea appeared over the past twenty years to integrate multi-disciplines (Munns et al. 2003; Sekizawa and Tanabe 2005) and the integrated databases (Fedra 1998) to provide a systematic overview of the sources of risks or hazards. In the framework, "integrated risk assessment" has been developed to be *integrated disaster risk reduction*. In a sense, the bureaucrats are more interested in how to get more resources to reduce disaster risk, rather than to know what is integrated risk caused by multi-hazards, such as both of earthquake and flood.

Until today no body really knows if the integrated risk assessment is always better than the classical risk assessment before we use. And, there are quite a few researchers interested in distinguishing between *integrated "risk assessment"* and *"integrated risk" assessment*. Therefore, there is not any commonly accepted approach to assess integrated risk of multi-hazards.

In this paper, in a point of view of probability risk, we define the integrated risk of multi-hazards. Reviewing some efforts in theoretically combining random variables, we develop the information diffusion technique to construct a discrete probability distribution and a discrete disaster function to assess an integrated risk caused by two hazards.

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2 INTEGRATED RISK CAUSED BY MULTI-HAZARDS

Risk, similar as a ghost, is a scene in the future associated with some adverse incident (Huang and Ruan, 2008). If we can accurately predict the scene, it is called a pseudo risk. In the case, it is not a wandering ghost, but a familiar thing. For example, if a person falls to the ground from a plane in 500 meters high without parachute, he will die. There is not any suspense, it is a pseudo risk. 77% of the risk definitions are suggested with the probability, which is employed to measure random uncertainty. It implies that, the most of risk analysts are interested in probability risks, which can statistically predict by using probability models with a lot of data. For example, there are powerful probability models and a lot of data to study traffic incidents. To accident insurance, the traffic incident is a probability risk.

There are three methods to profile a probability risk. The first is risk = (Event, Loss, Probability) generally in a tabular format; the second is risk matrix, it can be constructed in two ways; and the third is risk curve (real probabilistic loss distribution). Particularly, when the connotation of a probability risk is defined as the expected value of disaster, the risk is represented as:

$$Risk = \int_{u_0}^{u_1} f(x)p(x)dx \qquad (1)$$

where $p(x)$ is the probability distribution about an index x measuring adverse event, such as earthquake or flood, and $f(x)$ is the disaster function caused by x. u_0 is the minimum of x that could cause a disaster, and u_1 is the maximum of x that would occur. For example, if x is employed to measure earthquake magnitude occurred in China, u_0 is 4.5 and u_1 is 8.5.

Extending equation (1), we formally give the definition of an integrated probability risk of multi-hazards as the following.

Definition 1 Let $x_1, x_2, ..., x_n$ be n random variables for measuring n hazards, respectively. Let $p(x_1,x_2,...,x_n)$ be the joint probability distribution of the n random variables, $f(x_1,x_2,...,x_n)$ be the disaster function caused by the n hazards, and $u_0^{(x_i)}, u_1^{(x_i)}$ be the minimum and maximum of the i-th hazard, respectively, i=1,2,…,n. The expected value of disaster is called the integrated risk caused by n hazards, represented as:

$$Risk = \int_{u_0^{(x_1)}}^{u_1^{(x_1)}} \int_{u_0^{(x_2)}}^{u_1^{(x_2)}} \cdots \int_{u_0^{(x_n)}}^{u_1^{(x_n)}} f(x_1, x_2, \cdots, x_n) p(x_1, x_2, \cdots, x_n) dx_1 dx_2 \cdots dx_n \qquad (2)$$

It is necessary to verify whether a probability distribution and a disaster function are reliable before they can be employed to assess a probability risk. For example, we suppose that a set of observations of earthquake magnitude x and loss y is recorded in the past T years. The set as a sample provides statistical data to estimate a probability distribution of earthquake magnitude x occurring, denoted as $p(x)$, and to estimate a loss function as a relationship between x and loss y, denoted as $y=f(x)$. There are a lot of models are recommended for estimating probability distributions, and there is a sea of models are suggested for estimating input-output relation functions. Some have been demonstrated with practical effects, and others would be proven by using mathematical theory.

However, when the type of the population from which the sample is drawn is unknown, it is impossible to precisely estimate the underlying probability distribution. When the size of the sample of input-output observations is small, it is difficult to reasonably estimate the underlying input-output relation function.

Particularly, to multivariate random variables $x_1, x_2,..., x_n$, it is more difficult to estimate $p(x_1,x_2,...,x_n)$ and $f(x_1,x_2,...,x_n)$ with traditional statistical methods.

Despite the difficulties to estimate joint probability distributions, many researchers are hard working to do that. A key limitation of the existing parametric methods is that the distribution needs to be assumed a priori. Evidently, this is a strong assumption, since the form of the distribution is frequently unknown. Even the nonparametric models still make some assumptions regarding the form of the distribution. In addition, the nonparametric methods have other limitations (Alghalith, 2016; Talamakrouni *et al*, 2016).

The current popular approach is “copulas”. Copulas are functions that fully define the multivariate distribution of a random vector or a set of random variables (Nelsen, 2006). They link or join multivariate distributions functions of random variables to their univariate marginal distributions. According to Sklar’s theorem (Sklar, 1959; Salvadori et al., 2007), any multivariate joint distribution can be written in terms of a copula function and marginal distribution functions. However, the existence of a copula function does not mean that we can get it. There are a lot of copula models to construct a copula function with given marginal distribution functions, such as Gaussian copulas and Archimedean copulas. There are many families of Archimedean copulas, such as Frank, Gumbel, Clayton, which are uniparametric (Montes-Iturrizagaand Heredia-Zavoni, 2016). Estimating marginal distribution functions, finding an applicable copula function more difficult!

To estimate a disaster function $f\ (x_1,x_2,\ldots,x_n)$, the most coarsest method is multiple linear regression, the more popular is bio inspired computing, such as neural networks, leaping frog and bat algorithm. All of these algorithms try to replicate the way biological organisms and sub-organism entities operate to achieve high level of efficiency, even if sometimes the actual optimal solution is not achieved (Kar, 2016). However, none bio-inspired algorithm is a practical universal algorithm. For example, it has been theoretically proven that multilayer neural networks using arbitrary squashing functions can approximate any continuous function to any degree of accuracy, provided enough hidden units are available (Hornik et al., 1989). However, the neural networks has the problem of becoming trapped in local minima, which may lead to failure in finding a global optimal solution (Marco and Alberto, 1992). Besides, the convergence rate of algorithm is still too slow even if learning can be achieved. When a trained neural network is performing as a mapping from input space to output space, it is a black box. This means it is not possible to understand how a neural system works, and it is very hard to incorporate human a priori knowledge into a neural network.

It is clear that an integrated probability risk caused by multi-hazards can be regarded as the expected value of disaster excited by a multivariate random variable and a multivariate disaster function. And, it is not easy to estimate a joint probability distribution and a disaster function with given sample.

There is no loss in generality when we suppose that the n in equation (2) is 2. In the case, the integrated risk caused by two hazards could be represented as:

$$Risk = \int_{u_0^{(x_1)}}^{u_1^{(x_1)}} \int_{u_0^{(x_2)}}^{u_1^{(x_2)}} f(x_1,x_2)\, p(x_1,x_2)\, dx_1 dx_2 \qquad (3)$$

When we discuss a bivariate random variable with two components x_1, x_2, their joint probability distribution

$$P(x_1,x_2) = \Pr(X_1 \le x_1, X_2 \le x_2) \qquad (4)$$

is defined by the probability of a product event：In a random trial, events $X_1 \le x_1$ and $X_2 \le x_2$ simultaneously occur.

Obviously, the probability of that two kinds of disasters, such as earthquake and flood, simultaneously occur in a region is almost zero. In other words, there is not bivariate random sample in the strict sense in terms of respective two hazards.

To understand the phenomena, let us consider an experiment that consists of tossing a dice and a coin at the same time. We will assign an indicator random variable to the result of tossing the coin. If it comes up head we assign 1 to the variable, and if it comes up tail we assign 0 to the variable. Consider the following random variables:

X_1: The number of dots appearing on the dice.

X_2: The sum of the number of dots on the dice and the indicator for the coin.

Strictly speaking, the probability of that the dice and the coin land at the same time is almost zero. In the strict sense of “simultaneously occur”, the experiment cannot give any bivariate random sample. In practice case of a random experiment, X_1 and X_2 are recorded after a trial. Extending the time length of a trial to be a year, we can regard the disaster events occurred in a year that occurred simultaneously.

Let W be a sample of observations on disaster D caused by two hazards S and Z in T years. We write the sample in equation (5).

$$W=\{(s_1,z_1,d_1),(s_2,z_2,d_2),\cdots,(s_T,z_T,d_T)\} \tag{5}$$

s_i and z_i represent the magnitudes of hazards S and Z in i-th year and d_i is the disaster caused by the hazards in the year.

An integrated probability risk caused by S and Z is considered as the expected value of disaster caused by the hazards. According to equation (3), we know that, it is necessary to estimate a joint probability distribution of S and Z, $p(s,z)$, and a disaster function $d=f(s,z)$. In the case of that the given sample W does not come from too many years, we employ the information diffusion technique to estimate $p(s,z)$ and $f(s,z)$ with the sample.

3 INFORMATION DIFFUSION TECHNIQUE

The concept of information diffusion (Huang, 1997) was proposal in function learning from a small sample of data (Huang and Moraga, 2004). The approximate reasoning of information diffusion was used to estimate probabilities and fuzzy relationships from scant, incomplete data for grassland wildfires (Liu et al., 2010). The simplest models of information diffusion technique are the linear information distribution and the normal diffusion. The latter is more convenient to use. Mathematically, the normal diffusion can be illustrated in fuzzy set as the following (Huang, 2002).

Let $W=\{w_i \mid i=1,2,\cdots,m\}$ be a given sample and let $U=\{u\}$ be its universe. The function in equation (6) is called a normal diffusion function.

$$\mu(w,u)=\exp[-\frac{(w-u)^2}{2h^2}],\quad w\in W,u\in U. \tag{6}$$

The diffusion coefficient h can be calculated by using equation (7) (Huang, 2012)

$$h=\begin{cases}0.8146\,(b-a), & m=5;\\ 0.5690\,(b-a), & m=6;\\ 0.4560\,(b-a), & m=7;\\ 0.3860\,(b-a), & m=8;\\ 0.3362\,(b-a), & m=9;\\ 0.2986\,(b-a), & m=10;\\ 2.6851(b-a)/(m-1), & m\geq 11.\end{cases} \tag{7}$$

where $b=\max\{w_i\}$ and $a=\min\{w_i\}$.

Using a diffusion function, $\mu(w,u)$, we can change a given sample point w into a fuzzy set with membership function $\mu_w(u)=\mu(w,u)$ on universe U. The principle of information diffusion guarantees that there are reasonable diffusion functions to improve the non-diffusion estimates when the given samples are incomplete.

When we employ the normal diffusion to estimate a probability distribution, it is just the same as the Gaussian kernel estimate. It implies that Gaussian kernel connects to some simple diffusion without birth-death phenomenon. However, the coefficient from the kernel theory is both non-explanatory and rough. When the size *m* of a given sample is small, the method of normal diffusion is superior with respect to almost any distribution.

When we employ the information diffusion technique to estimate an input-output relation function with a given sample, the first of all is to construct an information matrix with the sample.

Let

$$X = \{(x_i, y_i) \mid i = 1,2,\cdots,m\} \tag{8}$$

be an *r*-dimensional random sample with input x_i and output y_i, and the input and output monitoring spaces of *X* be *U* and *V*, respectively, denoted as

$$\begin{cases} U = \{u_j \mid j = 1,2,\cdots,J\} \\ V = \{v_k \mid k = 1,2,\cdots,K\} \end{cases} \tag{9}$$

The monitoring spaces serve for diffusing with some steps. For a sample point (x_i, y_i) and a monitoring point (u_j, v_k), with a diffusion function μ, we can obtain a value $\mu((x_i, y_i),(u_j, v_k))$, called *diffused information* on (u_j, v_k) from (x_i, y_i), denoted as q_{ijk}.

Let

$$Q_{jk} = \sum_{i=1}^{m} q_{ijk} \tag{10}$$

$$Q = \begin{array}{c c} & \begin{array}{cccc} v_1 & v_2 & \cdots & v_K \end{array} \\ \begin{array}{c} u_1 \\ u_2 \\ \cdots \\ u_J \end{array} & \begin{pmatrix} Q_{11} & Q_{12} & \cdots & Q_{1K} \\ Q_{21} & Q_{22} & \cdots & Q_{2K} \\ \cdots & \cdots & \cdots & \cdots \\ Q_{J1} & Q_{J2} & \cdots & Q_{JK} \end{pmatrix} \end{array} \tag{11}$$

is called an information matrix of *X* on $U \times V$.

Then, according to the characteristic of the information matrix, we can change it to be a fuzzy relationship matrix. With an appropriate approximate reasoning operator, we can estimate the input-output relation function with respect to the given sample in equation (8).

4 JOINT DISTRIBUTION CONSTRUCTED BY 2-DIMENSION NORMAL DIFFUSION

From the sample in equation (5), we can have a sample of observations on hazards *S* and *Z* in *T* years. We write the sample in equation (12).

$$W_1 = \{(s_1, z_1),(s_2, z_2),\cdots,(s_T, z_T)\} \tag{12}$$

We employ *S* and *Z* to denote universes of the two hazards respectively:

$$\begin{cases} S = \{u_j \mid j = 1,2,\cdots,J\} \\ Z = \{v_k \mid k = 1,2,\cdots,K\} \end{cases} \tag{13}$$

The 2-dimension normal diffusion of W_1 on $S \times Z$ is defined in equation (14).

$$\mu((s_i,z_i),(u_j,v_k))=\exp[-\frac{(s_i-u_j)^2}{2h_s^2}]\exp[-\frac{(z_i-v_k)^2}{2h_z^2}], i=1,2,\cdots,T;\ j=1,2,\cdots,J;\ k=1,2,\cdots,K \tag{14}$$

The diffusion coefficient h_g, $g\in\{s,z\}$, can be calculated by using equation (15).

$$h_g=\begin{cases}0.8146(b_g-a_g), & T=5\\ 0.5690(b_g-a_g), & T=6\\ 0.4560(b_g-a_g), & T=7\\ 0.3860(b_g-a_g), & T=8\\ 0.3362(b_g-a_g), & T=9\\ 0.2986(b_g-a_g), & T=10\\ 2.6851(b_g-a_g)/(T-1), & T\ge 11\end{cases}. \tag{15}$$

where $b_g=\max_{1\le i\le T}\{g_i\}$ and $a_g=\min_{1\le j\le T}\{g_i\}$; for $g=s, g_i=s_i$; for $g=z, g_i=z_i$.

Then, using equation (17),

$$P(u_j,v_k)=\frac{\sum_{i=1}^{T}\mu((s_i,z_i),(u_j,v_k))}{\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{i=1}^{T}\mu((s_i,z_i),(u_j,v_k))} \tag{17}$$

we can obtain a joint probability distribution $P(u_j,v_k)$ which is a discrete function.

In above algorithm to estimate $P(u_j,v_k)$, we ignore the normalizing to unity $\mu((s_i,z_i),(u_j,v_k))$ on $S\times Z$ to guarantee that every diffused observation $\mu((s_i,z_i),(u_j,v_k))$ is equally important for constructing a joint distribution, because we can set discrete points (u_j,v_k) so much to reduce the difference.

5 DISASTER FUNCTION CONSTRUCTED BY 3-DIMENSION NORMAL DIFFUSION

The sample W of observations in equation (5) is a 3-dimension random sample with hazards input (s_i,z_i) and disaster output d_i, i=1,2,…,T. We employ the 3-dimension normal diffusion to estimate a disaster function.

Firstly, we employ S, Z and D to denote universes of the two hazards and the disaster, respectively:

$$\begin{cases}S=\{u_j\mid j=1,2,\cdots,J\}\\ Z=\{v_k\mid k=1,2,\cdots,K\}\\ D=\{o_l\mid l=1,2,\cdots,L\}\end{cases} \tag{18}$$

The 3-dimension normal diffusion of W on $S\times Z\times D$ is defined in equation (19).

$$\mu((s_i,z_i,d_i),(u_j,v_k,o_l))=\exp[-\frac{(s_i-u_j)^2}{2h_s^2}]\exp[-\frac{(z_i-v_k)^2}{2h_z^2}]\exp[-\frac{(d_i-o_l)^2}{2h_d^2}],$$
$$i=1,2,\cdots,T;\ j=1,2,\cdots,J;\ k=1,2,\cdots,K;\ l=1,2,\cdots,L. \tag{19}$$

where the diffusion coefficient h_g, $g\in\{s,z,d\}$, also be calculated by using equation (15).

Secondly, let

$$Q_{jkl}=\sum_{i=1}^{T}\mu((s_i,z_i,d_i),(u_j,v_k,o_l)),\ j=1,2,\cdots,J;k=1,2,\cdots,K;l=1,2,\cdots,L. \tag{20}$$

We obtain an information matrix of W on $S\times Z\times D$ shown in equation (21).

$$Q=\left(\begin{array}{ccc} & & \begin{array}{cccc} d_1 & d_2 & \cdots & d_L \end{array} \\ v_1 & \begin{array}{c} u_1 \\ u_2 \\ \vdots \\ u_J \end{array} & \begin{bmatrix} Q_{111} & Q_{112} & \cdots & Q_{11L} \\ Q_{211} & Q_{212} & \cdots & Q_{21L} \\ \vdots & \vdots & \vdots & \vdots \\ Q_{J11} & Q_{J12} & \cdots & Q_{J1L} \end{bmatrix} \\ v_2 & \begin{array}{c} u_1 \\ u_2 \\ \vdots \\ u_J \end{array} & \begin{bmatrix} Q_{121} & Q_{122} & \cdots & Q_{12L} \\ Q_{221} & Q_{222} & \cdots & Q_{22L} \\ \vdots & \vdots & \vdots & \vdots \\ Q_{J21} & Q_{J22} & \cdots & Q_{J2L} \end{bmatrix} \\ \vdots & \vdots & \vdots \\ v_K & \begin{array}{c} u_1 \\ u_2 \\ \vdots \\ u_J \end{array} & \begin{bmatrix} Q_{1K1} & Q_{1K2} & \cdots & Q_{1KL} \\ Q_{2K1} & Q_{2K2} & \cdots & Q_{2KL} \\ \vdots & \vdots & \vdots & \vdots \\ Q_{JK1} & Q_{JK2} & \cdots & Q_{JKL} \end{bmatrix} \end{array}\right) \tag{21}$$

$\forall l\in\{1,2,\cdots,L\}$, let

$$H_l=\max_{\substack{1\le j\le J\\1\le k\le K}}\{Q_{jkl}\} \tag{22}$$

$$r_{jik}=Q_{jkl}/H_l,\quad j=1,2,\cdots,J;k=1,2,\cdots,K \tag{23}$$

then

$$R=\{r_{jkl}\}_{J\times K\times L} \tag{24}$$

is a fuzzy relationship between input (s,z) and output d .

For a fuzzy input A with membership function $\mu_A(u_j,v_k),\quad u_j\in S,v_k\in Z$, employing the approximate reasoning operator represented in equation (25), we can obtain a fuzzy output B with membership function $\mu_B(o_l),\quad o_l\in D$.

$$\mu_B(o_l)=\max_{\substack{1\le j\le J\\1\le k\le K}}\min\{\mu_A(u_j,v_k),r_{jkl}\} \tag{25}$$

Finally, using the center-of-gravity method, we obtain a crisp value $d(u_j,v_k)$:

$$d(u_j,v_k)=\left(\sum_{l=1}^{L}\mu_B(o_l)o_l\right)\Bigg/\left(\sum_{l=1}^{L}\mu_B(o_l)\right) \tag{26}$$

The $d(u_j,v_k)$ is the disaster function constructed by 3-dimension normal diffusion with the given sample W in equation (5). It is a discrete function.

6 INTEGRATED RISK CALCULATED BY JOINT DISTRIBUTION AND DISASTER FUNCTION

Recalling equation (2) and considering the joint distribution and disaster function we obtained are discrete, we calculate the integrated risk by using formula (27).

$$Risk = \sum_{j=1}^{J}\sum_{k}^{K} d(u_j, v_k)P(u_j, v_k) \tag{27}$$

where $P(u_j, v_k)$ and $d(u_j, v_k)$ are given in equations (17) and (26), respectively. The physical meaning of the "*risk*" in (27) is the expected value of disaster, which is assessed by using the sample of observations on disaster *D* caused by two hazards *S* and *Z* in *T* years, shown in equation (5).

As we know that, a risk is a scene in the future associated with some adverse incident. When we use a random sample to assess a risk, we are in fact using the past to judge the future because the observations of the sample record historical events occurred in a stochastic system. The reliability of the assessment depends on the assumption that the stochastic system evolving over time in the study period is a stationary Markov process.

In probability theory, a Markov process is a stochastic process that has the property that the next value of the Markov process depends on the current value, but it is conditionally independent of the previous values of the stochastic process. A Markov process is a stationary Markov process if the moments are not affected by a time shift. In other words, the stochastic behavior of the system in the future is the same as the stochastic behavior in the past.

In fact, most of disaster systems are in change, the corresponding stochastic processes do not satisfy the stationary Markov process hypothesis. If we collect observations of historical disasters across hundred years to assess disaster risks, the reliability of the assessments will be low.

When we use a traditional statistical method, such as parameter estimation method, to assess a risk caused by a hazard, if the observations are across 30 years, the result of the risk assessment would have some degree of reliability. However, to an integrated probability risk caused by two hazards, the size of a sample with observations across 30 years is too small. To estimate the joint distribution in equations (17) we need about 900 (i.e. 30×30) observations if we require that the result has some degree of reliability.

We believe that, for most regions, the observations used for assessing an integrated risk should not span more than 50 years. They are incomplete information to estimate the joint distribution and the disaster function. It is quite good for us to obtain a discrete joint distribution $P(u_j, v_k)$ and a discrete disaster function $d(u_j, v_k)$ to estimate an integrated risk. When we have to make a choice between theoretical perfection and respect for reality, we should respect the reality to carry out the risk assessment.

7 CONCLUSION AND DISCUSSION

It is important to distinguish *integrated "risk assessment"* and *"integrated risk" assessment*. An integrated probability risk of multi-hazards is the expected value of disaster, which is determined by a joint probability distribution and a disaster function.

When the type of the population from which the sample is drawn is unknown, it is difficult to estimate the distribution and the function. There are a lot of copula models to construct a copula function to be a joint probability distribution with given marginal distribution functions. Nobody knows which constructed distribution from "copula" should be one better to assess the integrated probability risk.

The information diffusion technique regards small samples as fuzzy information. It can be employed to construct a discrete joint probability distribution and a discrete disaster function for assessing integrated probability risks.

The proposed approach does not need to know the distribution type of the population from that the given sample is drawn, nor need to know the function form of the causal relationship, which can construct joint probability distribution and disaster function with clear physical meaning. So that, although the assessed risk is not accurate, but more credible.

Due to limited length of this paper, a case study is omitted. It will be given in an extended version.

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