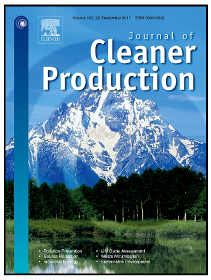

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Risk management of extreme events under climate change

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Abstract

Risk management is an effective way to mitigate the adverse consequences of extreme events, and plays an important role in climate change adaptation. On the basis of the literature, this paper presents a conceptual framework for managing the risk of extreme events under climate change, and accordingly summarizes the recent developments with a focus on several key topics. In terms of risk determinants, the impacts of climate variability on the frequency of extreme events are addressed, and the various meanings and measurements of specific vulnerability are compared. As for the process of risk management, the dynamic assessment approach regarding future climate condition is emphasized. Besides, in view of decision making the available means to enhance the effectiveness of adaptation and mitigation strategies are highlighted. Finally, uncertainty is discussed with respect to its sources and solution.

Keywords: *climate change, extreme events, risk management, adaptation, uncertainty*

1 INTRODUCTION

Climate change may cause serious impacts on human-environmental system, and is an integrated scientific issue which challenges the world (IPCC, 2014). It is reported that the changing climate may result in more extreme events worldwide, so that there would be heavier socioeconomic damages (IPCC, 2012; Rummukainen, 2012; Yuan et al., 2016). This is receiving more attention from the public, and especially the governments and research scholars have been devoted to exploring effective measures to mitigate adverse consequences.

Risk management is an available way to timely cope with extreme events (Nam et al., 2012). Different from traditional idea, it aims to emphasize preparedness and provide appropriate strategies according to the extent of damage. In the context of climate change, the occurrence of extreme event and socioeconomic development appear to own high uncertainty with varying time and space. This suggests that risk management is of great significance to help alleviate the impacts of weather-related extremes, and of necessity in adaptation to climate change (IPCC, 2012; Kunreuther et al., 2013).

It is argued that the risk of climate change, which mainly arises from extreme events, reflects the interactions between hazard and vulnerability in a particular condition which integrate natural and social sciences (Blaikie et al., 1994; UN/ISDR, 2004). Thus, risk management of extreme events under climate change is regarded as an interdisciplinary problem, and there have been some discussions in different aspects.

The cause of risk is attributed to hazardous physical event whose variations are expected to influence the components of risk management. With global environmental change, therefore, there are more complicated characteristics of risk management of extreme events, and practically these bring out some bigger challenges. First, it is required to analyze the effects of climate change on extreme events and the associated consequences of human-environmental system. This refers to risk assessment which attempts to describe climate change risk with qualitative and quantitative methods. Second, it needs to detect the ways to set up coping strategies with diverse information and knowledge, and the adoption of adaptive behavior in practice. This relates to damage adaptation and mitigation which intend to reduce and control the risk of extreme events. Finally, the uncertainty should be considered with respect to the possible impacts and solutions because of its essential role in risk management.

This paper aims to highlight the features of climate change risk, and address the advances in risk management. The crucial components in risk management are identified based on a bibliometric analysis. Accordingly, a conceptual framework for risk management of extreme events under climate change is presented to summarize recent developments with a focus on some key topics.

2 CONCEPTUAL FRAMEWORK

The bibliometric analysis is made with the data collected from Web of Science. On the basis of the literature a conceptual framework for risk management of extreme events considering climate change effect is given as Figure 1.

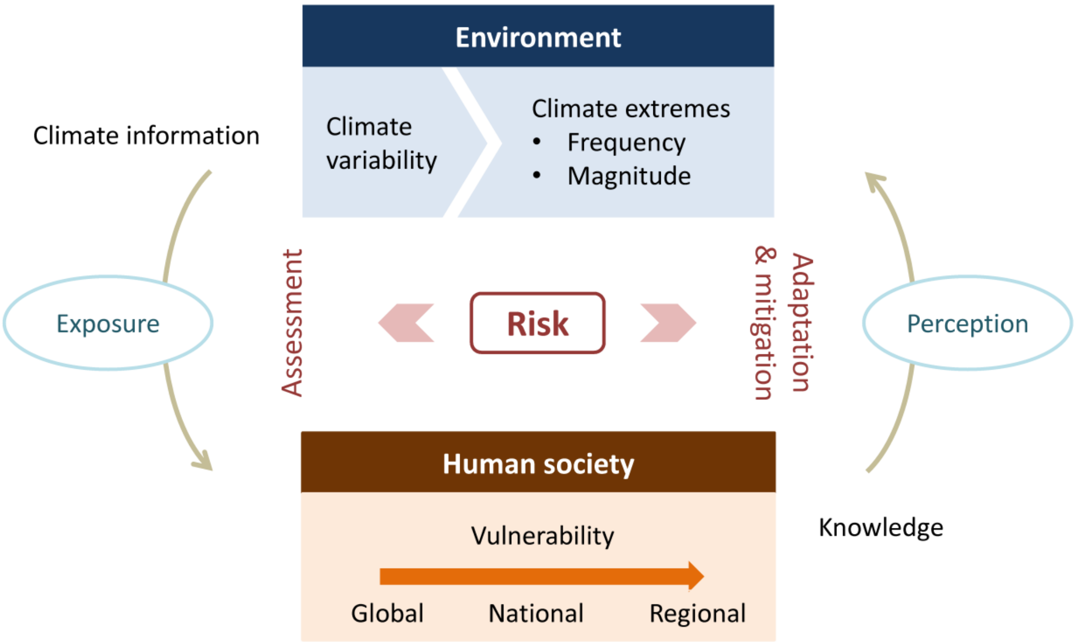

Figure 1 Conceptual framework for risk management of extreme events under climate change (adapted from Turner et al. (2003); UN/ISDR (2004); IPCC (2012))

For risk management, the basic work is to address how to characterize risk and how to deal with risk. These eventually refer to risk assessment and risk adaptation and mitigation. The risk of extreme events, which results from the interactions between climate and human society, consists of three primary components including hazard, exposure, and vulnerability (IPCC, 2012). Here hazard refers to various kinds of climate extremes, and its extent is often characterized by frequency and magnitude. Climate variability can directly influence natural environment on both temporal and spatial dimensions, so that there would be changes in the statistical characteristics of extreme events. These affect human society via particular exposure, and thus vulnerability is commonly defined as the degree to which a system is likely to be adversely affected (Adger, 2006). Notably, vulnerability at different scales actually carries diverse information (Fekete et al., 2010). This requires the integration of multi-level information in vulnerability analysis.

Risk assessment synthesizes hazard, exposure, and vulnerability to map risk with qualitative and quantitative methods. Hazard analysis and vulnerability analysis are two basic processes to find the relationship between the extent of extreme event and its probability of occurrence and the relationship between the extent of extreme event and the magnitude of consequence respectively. Therefore, the outcomes of risk assessment have various types. For example, risk classification is a quantitative form that reveals the differences in risk level across areas (Yuan et al., 2015a). This facilitates the exploration of risky nations and regions at the macro-level. Yet, risk curve quantifies the relationship between the probability of occurrence of extreme event and the magnitude of consequence to provide more detailed information for risk description. Due to climate variability and socioeconomic development, the dynamic risk assessment regarding future climate condition is of greater practical significance.

To mitigate and adapt to climate change risk, the structural and non-structural measures are adopted. Structural interventions concern the optimized plan developed by cost-benefit analysis and portfolio according to risk level. As a result, this requires to figure out the acceptable ranges of risk. As for an individual, there are several factors playing key roles in choosing adaptation and mitigation strategies, such as risk preference, risk perception, living experience, and living condition. High risk awareness makes more adaptive behavior such as buying insurance, reducing asset exposure, and preparing emergent facilities, and these could help promote the effectiveness of damage reduction.

Two elements, climate information and knowledge, need to be highlighted in risk management of extreme events under climate change. When making decisions, policy makers, managers, and individuals all rely on climate information which are required to be not only useful but also usable

(Lemos et al., 2012). Delivering accurate information could make better strategies and more benefits. In addition, it is argued that human knowledge, which refers to both scientific knowledge and local experience, is necessary during this process. Therefore, it requires more participants with various knowledge and the integration of diverse information to enhance the objectivity of risk assessment and the effectiveness of mitigation and adaptation strategies.

3 FREQUENCY OF EXTREME EVENTS WITH CLIMATE VARIABILITY

The natural environment is altered by climate variability from two dimensions: for the average climate variable may have a long-run trend, while for the fluctuation there may be a wider range with more extreme values (IPCC, 2013). These essentially bring out the changes in the statistical characteristics of climate variables (Morss et al., 2011; Rummukainen, 2012).The frequency of extreme events is of concern to risk management. It is used to represent the extent of hazard in risk assessment, and also provides the basis for mitigation and adaptation strategies such as engineering construction and premium rate. It is a basic work for managing climate change risk that estimating the frequency curve of extreme event and the associated variation.

The series of extreme values is usually obtained by block maxima (BM) method and peaks-over-threshold (POT) method (Coles, 2001). BM method picks up extreme value within a fixed period, however, it often has insufficient samples in some regions due to partial information used only. POT method uses a threshold to identify extreme value in the entire data set, which eventually increases samples and decreases estimation bias. Traditional frequency analysis method assumes that the extreme values are identical, i.e. they come from the same condition. However, climate variability makes it difficult to completely conform to such an assumption. This may reduce the reliability of the estimates of extreme event frequency and threaten the effectiveness of measures for risk management (Gilroy and McCuen, 2012).

In previous studies, some non-stationary frequency analysis approaches have been developed (Khaliq et al., 2006; Olsen, 2006). A common way is to introduce external factors into the distribution function of extreme values so as to reveal dynamic characteristics. On the temporal dimension, the time-varying parameters in distribution function are constructed when there are significant periodic and long-term variations. The frequency curve changing with time indicates temporal dynamics (Mendez et al., 2007; Roth et al., 2012; Wi et al., 2016). On the environmental dimension, the parameters are usually coupled with climate variable according to the relationship between extreme event and climate mode. The frequency curve containing climate information implies the dynamics in the changing condition (Du et al., 2015; Katz et al., 2002; Lopez and Frances, 2013; Silva et al., 2016).

As a result, future frequency curve is obtained on the basis of the varying distribution function by extrapolating external driving force (Gilroy and McCuen, 2012; Mudersbach and Jensen, 2010). Note that there needs to be a reliable relationship between function parameter and the associated driving factor. In addition, frequency curve can also be derived from a set of extreme values simulated by physical models during a future period (Ngongondo et al., 2013; Raff et al., 2009). Nevertheless, its accuracy highly depends on model outputs.

4 VULNERABILITY

Vulnerability is a central concept in climate change risk research. From different perspectives, there are significant differences in the research object, meaning, and measurement of specific vulnerability.

Physical vulnerability is formed in accordance with the dose-response chain which focuses on physical damage caused by extreme event. The object in physical vulnerability assessment is natural-environmental system, and the physical process of extreme event essentially reflects vulnerability. It reveals the input-output relationship in natural environment system, that is, the extent of hazard relates to the magnitude of damage (Wang et al., 2013). Such a relationship is commonly defined as vulnerability curve which is calculated by simulating different scenarios based on physical models. For example, the crop production would be affected by drought event, and thus we can simulate a variety of yield losses in the associated drought conditions. Accordingly, this relationship between production losses and drought event (represented by drought hazard index) implies vulnerability (Yue et al., 2015).

Social vulnerability emphasizes on sensitivity and adaptive capacity to extremes, and refers to several influences such as population characteristics, economic development, resources and environment, and living conditions. Therefore, the difference in social vulnerability, to some extent, implies the inequalities between regions (Cutter et al., 2003; Cutter and Finch, 2008; Martinich et al., 2013). Different from physical vulnerability, social vulnerability is usually regarded as an independent status irrelevant to extreme event, and theoretically applicable to all scenarios under climate change (Emrich and Cutter, 2011). Indicator-based method is widely used for social vulnerability measurement. Zou and Wei (2010) employed meta-analysis method to determine the driving factors of vulnerability. In a direct way, those selected indicators are aggregated with equal/unequal weights (Lee, 2014). Yet, social vulnerability is commonly characterized by a variety of indicators indeed. Due to the potential complicated interrelationships, the multi-level indicators can be decomposed into some key components for assessment with multivariable statistical analysis (Armas and Gavris, 2013; Frigerio and De Amicis, 2016; Mazumdar and Paul, 2016).

From a perspective of human-environmental system, vulnerability is more inclusive with natural, environmental, social, and economic aspects (Lee et al., 2013; Morss et al., 2011). The comprehensive vulnerability in a particular scenario is generally composed of exposure, sensitivity, and adaptive capacity (Krishnamurthy et al., 2011; Murthy et al., 2015; Wilhelmi and Morss, 2013). Yuan et al. (2015b) interprets vulnerability as the imbalance among the three components, that is, the excesses of exposure and sensitivity as well as the shortfalls of adaptive capacity. Wei et al. (2004) measures vulnerability from an input-output perspective. The indicators are combined by data envelopment analysis. Also, vulnerability curve is a common expression to describe the variation of vulnerability in the changing climate and socioeconomic conditions, and provides important information for risk reduction (Dawson et al., 2011).

Here we argue that more attention should be paid to the scales in vulnerability research. For example, the scale of research field determines the scope of objects, i.e. the physical, social, economic, cultural, and environmental dimensions (Kienberger et al., 2013). Temporal scale indicates the period in which vulnerability exists, while spatial scale fixes the area and location where vulnerability occurs (Fekete et al., 2010; Turner et al., 2003). These research scales set up the meaning, layers, and framework of vulnerability, and the particular variations at different scales are revealed. It could help understand the cause of climate change risk and make proper coping measures by integrating the multi-level information with top-down or bottom-up modelling.

5 RISK ASSESSMENT

Risk assessment is a key process in risk management of climate extremes. It aims to quantify risk and the associated temporal-spatial characteristics, and guide the development of adaptation and mitigation strategies. The current assessment features the dynamic variation of future risk considering the need for coping with climate change.

Dynamic risk assessment mainly relies on scenario simulation methods with the assumptions on the natural and social factors associated with climate, land, demography, economy, technology, and policy. Climate scenario reflects the extent of climate variability in the future which comes from the outputs of climate models. The large-scale climate data are downscaled to get high-solution regional projections by either statistical or dynamical methods. Socioeconomic scenario includes the developments in demography, economy, urbanization, and technology, and can be derived by extrapolating the indicators according to their historical variations. Policy scenario represents the planning at global, national, and regional levels including structural and non-structural measures (Dawson et al., 2011). Land scenario indicates the change in utilization type that is affected by geographic and socioeconomic conditions. For example, Cammerer et al. (2013) estimated the impacts of natural and social drivers on land patterns using statistical approach. The projected and assumed data are finally decomposed into the smallest cells in accordance to spatial scale (Linde et al., 2011; Yu et al., 2013).

Climate change risk results from the interaction between natural and social systems, and has the primary components of hazard, exposure, and vulnerability. In this paper, hazard refers to climate extremes whose variations are calculated with climate scenarios and disaster models. Exposure is the status exposed to the external environment of a particular unit, which is related to population, asset, land area, and so on (Jongman et al., 2012). Preston (2013) focused on the path dependence of socioeconomic exposure, so that the future changes were projected from the past trajectory. Furthermore, vulnerability curves are simulated under different scenarios (Bouwer, 2013; Ranger et al., 2011).

Most studies on dynamic risk assessment aim to get the scenario-based risk curves (Kirshen et al., 2012) which combine frequency analysis of extreme event and vulnerability analysis (Yuan et al., 2013). Thus, risk curve reveals the relationship between the occurrence probability of extreme event and its damages. As a matter of fact, the changes in risk curves with and without coping measures show the benefits of damage reduction plan. Instead of seeking the lowest risk, it is more practical to explore the acceptable ranges of risk on the basis of cost-benefit analysis considering the risk preference of decision maker.

6 ADAPTATION AND MITIGATION

Structural and non-structural measures are available for risk adaptation and mitigation, and there are lots of concrete contents for different sectors (Jones and Preston, 2011). The literature mainly concerns the decision processes of making and implementing strategies.

In the stage of making strategies, scientific knowledge and information are considered as crucial elements (Kiparsky et al., 2012; Pennesi et al., 2012), and especially the local knowledge is of particular experience for environmental change adaptation (Lebel, 2013; Naess, 2013; Reyes-Garcia et al., 2016; Xu and Grumbine, 2014). Participatory Integrated Assessment (PIA) is employed to integrate the diverse knowledge and information to enhance the quality of decision in risk management (Gaillard et al., 2013). Salter et al. (2010) summarized the methods, mechanisms, processes, and outcomes of PIA, and further emphasized that computer models were the necessary platform to realize quantitative outcomes. For example, the interactive communication gathers the knowledge and information of participants to form decision support systems for adaptation and mitigation strategies (Ceccato et al., 2011; Santoro et al., 2013). Importantly, the integration relies on the relationships between key influences of risk, and are completed by inference and simulation models, such as Bayesian decision network (Catenacci and Giupponi, 2013; Richards et al., 2016), collaborative modelling (Evers et al., 2016), and system dynamics modelling (Haase, 2013).

In the stage of implementing strategies, the effectiveness at the household level is dominantly determined by individual decision. The empirical results show that adaptive behavior is affected by two parts: (1) the objective factors include social and demographic attributions (e.g. gender, age, occupation, and education), economic attribution (e.g. income and price), and environmental attribution (e.g. geographic location, reliance on resources, and warning system); (2) the subjective factors refer to value, risk awareness, risk attitude, and risk perception (Bichard and Kazmierczak, 2012; Botzen et al., 2009, 2013; Combest-Friedman et al., 2012; Paul and Routray, 2011; Qasim et al., 2015; Tucker et al., 2010). Risk perception is the determinant motivating individual adaptive behavior (Grothmann and Patt, 2005). This is interpreted by Protection Motivation Theory which consists of threat and coping appraisals. Specifically, during the threat appraisal process the perceived risk is evaluated from severity, occurrence probability, consequence, vulnerability, and intrinsic and extrinsic rewards. Then, the coping appraisal is the process of thinking about the benefits of possible actions, which includes response efficacy, self-efficacy, and response cost (Bubeck et al., 2012; Koerth et al., 2013a; Reynaud et al., 2013; Terpstra, 2011). Previous studies illustrate that influencing factors such as personal emotions, knowledge, disaster experiences, and trust would have impacts on risk perception (Terpstra, 2011), however, there might be insignificant relationship between high perception and mitigation behavior (Bradford et al., 2012; Bubeck et al., 2012). Instead, the coping appraisal process seems to have a dominant effect (Koerth et al., 2013b). The explanation given by Bubeck et al. (2012) is that the investigation is influenced by early precautionary behavior, and actually risk perception is positively related to future mitigation behavior.

7 UNCERTAINTY

There are many uncertainties in climate change risk management, and basically they are attributed to nature, recognized bias, and ambiguity (Ekstrom et al., 2013; Walker et al., 2003). The nature indicates that uncertainty is the intrinsic characteristics of natural-social system caused by the complicated natural processes and human activities, e.g. atmosphere-ocean circulation, land use, and socioeconomic development. Recognized bias means that uncertainty is the outcome of the recognition of natural-social system, and shows the incomplete knowledge of inherent rules. It is closely related to data availability and accuracy, technology level, the completeness of knowledge, model structure and parameter, and so on. For example, climate model is used to simulate the natural variability based on historical data and recognized mechanism, but it still cannot reflect the real physical process exactly. The outcomes have uncertainties due to model structure, parameter selection, and calculation bias. Ambiguity implies that uncertainty comes from the difference in understanding and the lack of universally truth. It refers to subjective cognition. For instance, decision makers would have different choices based on their own recognitions and preferences as facing with some plans of similar effectiveness.

These uncertainties make higher difficulties in risk management, especially for coping with climate change. Recently, it is argued that robust decision is an effective way to deal with uncertainty. It attempts to detect the performances of possible results from a wide range of scenarios so as to evaluate the decision plan with robust rather than optimized criterion (Kunreuther et al., 2013; Ranger and Niehorster, 2012). Weaver et al. (2013) points out that robust decision is a process to improve the strategy which needs cooperation and wide participation. Thus, this would accelerate the movement of information from useful to usable in order to meet the demand of decision makers (Lemos et al., 2012). Meanwhile, Lemos and Rood (2010) suggests that in the context of high uncertainty decision makers should not look for perfect results, but seek different ways to manage uncertainty with knowledge systems.

8 SUMMARY

Climate change is one of the most important issue of concern to the public, and may cause serious impacts on society. Faced with possible more extreme events, managers try to feature preparedness to alleviate the adverse consequences. Risk management can provide timely strategies to mitigate potential damages. This paper presents a conceptual framework for risk management of extreme events under climate change to summarize recent developments with a focus on several key topics. The main points are summarized below.

The dynamic risk management of extreme events is desired with the effect of climate change. First, due to climate variability the non-stationary frequency analysis is needed for extreme events. On the temporal and environmental dimensions, a common way is to introduce varying variables into the distribution function to reveal the dynamic characteristics of frequency curves in the changing environmental conditions. Second, risk assessment is established on the dynamic processes associated with climate, society, economy, policy, and land use. The main outcome is risk curve revealing the relationship between the occurrence probability of hazard and the magnitude of adverse consequences, and its dynamic changes under different scenarios provide decision basis for adaptation and mitigation strategies.

Multi-level is an inherent attribution of climate change risk management. The research object and meaning of vulnerability are different from the global to regional level. Physical vulnerability considers the physical damages caused by hazardous event, while social vulnerability emphasizes sensitivity and adaptive capacity of social groups to extreme events. More commonly, vulnerability contains natural and social aspects. Decision makers should take full use of the information which indicates the particular characteristics of vulnerability at different temporal-spatial scales.

Uncertainty is the nature of risk management. With natural stochastic rules and limited knowledge the occurrence of extreme event cannot be predicted exactly, and climate change raises more uncertainties. To enhance the effectiveness of adaptation and mitigation strategies for climate change risk, it is important to not only promote individual adaptation, but also integrate the diverse information and knowledge to make robust decision.

The multi-hazard risk management needs to be developed in the future studies. In fact, the physical processes of extreme events are interrelated to cause impacts. This requires to consider the joint occurrence of extreme events to quantify risk. As mentioned above, climate change is likely to result in non-stationarity. Therefore, it is of great complexity to model the probability of multi-events. The conventional methods for univariate analysis are insufficient for risk assessment. In addition, it is a challenge to model the impacts of multi-hazard due to the complicated interactions. The extreme impacts caused by compound events are of concern to stakeholders. Thus, it is necessary to define the impact boundaries at the beginning of multi-risk assessment. On the other hand, we should pay more attention to the adaptation and mitigation to multi-hazard risk. Still, we argue that the integration of knowledge and information to make strategies is a crucial issue. With the probabilistic method, the uncertainty in decision-making is quantified. That helps produce robust plans for multi-risk management.

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A conceptual framework for managing disaster risk under climate change is presented.

Various meanings and measurements of specified vulnerability are compared.

The uncertainty is discussed with respect to its sources and solution.