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暴雨灾害链动态风险分析

DYNAMIC RISK ANALYSIS FOR RAINSTORM DISASTER CHAIN

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哈尔滨工业大学

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摘 要

在过去的三十年中，风险分析已经渗透到经济生活中的方方面面，成为了一种处理问题的有效辅助手段。在自然灾害方面，风险分析的研究尤其重要。风险研究不仅可以指导相关决策者做出正确的应急管理决策，而且能够在一定程度上减少由于自然灾害的发生给社会带来的负面影响。随着全球气候变化，许多地区接连遭受极端自然灾害，严重威胁着人们的生命、财产安全，同时快速的城市化进程增加了自然灾害发生的可能性。在气候变暖的大环境下，社会的发展迫切需要更加有效的灾害链风险评估方法，也就是多灾种风险评估。风险是衡量灾害发生的严重程度或灾害发生的可能性大小，传统的风险评估主要使用地理信息系统来绘制风险区域图，以及用信息扩散方法来评估不完整数据集下的期望风险。对于风险评估的研究，很少有文章讨论多灾种等级衡量标准中存在的模糊不确定性以及考虑时间维度下的动态风险。其次由于收集到的历史样本数据很少，记录的数据维度不够，会造成数据的不完备性。上述两个问题的出现加大了风险评估的困难性，本研究基于期望风险的定义提出了可变模糊集信息扩散动态风险评估模型，同时用该模型来评估深圳地区台风暴雨灾害的动态风险。

针对多灾种动态分析评估中的模糊区间和信息不完备问题，文中构建了可变模糊集信息扩散动态风险评估模型。顾名思义，该模型是将模糊集理论和信息扩散理论相结合，旨在解决数据不完备情况下，多灾种动态风险评估所出现的模糊不确定性问题。其中可变模糊集理论主要是消除评估标准当中的不确定性,得到多灾种等级的综合评估结果。信息扩散理论主要针对小样本数据集中包含的不完备信息，解决小样本数据下估计结果精度不高这一问题。文中建模过程如下：首先基于概率风险定义，考虑时间因素引入动态概率风险，并在此定义下给出动态风险的计算表达式。其次由于多灾种等级衡量结果往往会带有不确定性，模型结合可变模糊集和信息熵方法，将多灾种的衡量指标转换为单一数值来表示多灾种等级。该方法不仅给出相对隶属度计算的过程，而且提高了多灾种风险评估的准确性。然后基于上述模型所得到的多灾种等级值结果，文中模型利用时间数据以及灾损大小，使用信息扩散方法估计灾害发生的条件概率分布和脆弱性曲线。该方法通过将样本点转化为模糊集来提高样本数据估计条件概率分布与脆弱性曲线估计的准确性，以此解决动态风险当中的不完备信息问题。最终根据期望概率公式计算动态风险，结合正态扩散所得到的灾害等级概率分布和承灾体脆弱性曲线给出多灾种的动态概率风险。文中所构造的可变模糊集信息扩散动态风险评估模型综合考虑了多灾

种等级评估指标的多样性，在不完备数据集下提高了动态风险计算的准确性。其主要创新点在于：(i) 根据动态风险评估这一研究对象，考虑时间因素引入动态概率风险定义。(ii) 针对多灾种评估中不同灾种的评估具有不一样的衡量指标这一问题，结合可变模糊集和信息熵方法，将多灾种的衡量指标转换为单一数值来表示多灾种灾害等级。(iii) 基于动态概率风险的定义，将得到的灾害等级和灾害损失数据使用信息扩散方法求解各类灾害等级对应的条件概率分布与脆弱性曲线。(iv) 结合正态扩散所得到的灾害等级概率分布和承灾体脆弱性曲线给出了多灾种的动态概率风险。为了阐述可变模糊集信息扩散动态风险评估模型的可行性，文中用此模型来评估深圳地区的台风暴雨灾害动态风险，并由此给出应急管理建议。

沿海城市深圳属于亚热带海洋季风气候，台风暴雨灾害严重制约了当地经济和社会的可持续发展。据统计，从 1990 年至 2016 年间深圳地区的台风和暴雨灾害，平均来说造成 3.4 人死亡，14.9 万人受灾，直接经济损失超过 1.36 亿元人民币。然而，对于该地区的自然灾害风险评估，很少以定量方式评估台风暴雨灾害对于深圳地区的影响。本研究通过阅读气象年报和查阅台风网的相关信息，收集到台风暴雨灾害发生时对应的最值降水，强风强度、台风登陆点以及直接经济损失数据。根据可变模糊集信息扩散动态风险评估模型，文中首先根据台风暴雨灾害的四级分类标准，使用可变模糊集和信息熵方法来综合刻画台风暴雨灾害的等级，结果表示深圳地区受到台风暴雨灾害影响的等级主要是 III 类。其次在时间变量下，将得到的灾害等级数据和直接经济损失使用信息扩散方法计算对应灾害等级发生的条件概率密度和承灾体脆弱性曲线。最后根据期望风险的定义计算台风暴雨灾害发生的动态风险大小。结果显示：(i) 台风暴雨灾害等级可以分为 4 类，对深圳地区来说，台风暴雨灾害集中发生于八、九月份，且 II、III 类灾害在过去 8 年中发生的概率最高。(ii) 从灾损角度来看，经济损失集中于八、九月份，这两个月发生的各种等级灾害对经济造成的损失最大。不同月份同一等级灾害造成的直接经济损失不相同，这说明台风和暴雨对经济的影响不完全相同。同一月份下，随着灾害等级不断升高，对深圳地区造成的经济损失程度在逐渐减弱，这说明深圳地区承灾能力阈值比较大，在现有体系下应对突发性灾害的能力比较强。(iii) 不同月份下，台风暴雨灾害给深圳地区带来的风险程度不一样，八、九月份灾害风险程度最高，平均来说这两个月所带来的经济损失分别为 1.14 亿元和 1.67 亿元。综合之前的灾害等级分布月份可知，这个结论比较符合深圳地区的自然灾害的分布情况，能对灾害应急管理给出一定的指导性意见。

关键词：动态风险评估；暴雨灾害链；可变模糊集；相对隶属度；信息扩散方法

Abstract

Risk analysis has emerged as an effective and comprehensive procedure that supplements and complements the overall economy during the past three decades. In terms of natural hazards, research on risk analysis is crucially important for decision makers to implement emergency management policy, which can reduce negative impacts on society to certain extent. With the global climate change, many cities have suffered extreme natural hazards more frequently. At the same time, human activities, such as the growth of settlements, contribute to increasing the probability of the adverse impacts of natural hazards. The development of society urgently needs more effective hazard chain risk assessment methods, or multiple hazards risk evaluation models, especially under the circumstance of climate change. Risk is defined as a measure of the severity of hazards, or a measure of the probability of adverse effects. Traditional methods of assessing risks mainly utilize Geographic Information System to get risk map, and information diffusion method to deal with incomplete data sets. However, there are few papers discussing the uncertainty of multiple hazards and considering dynamic risk under time dimension. Besides, in the existing study for dynamic risk evaluation, the collected data are limited with insufficient data dimensions. Considering the above mentioned research gaps, this research proposes a brand-new model to evaluate multiple hazards dynamic risk and applies it to study typhoons and rainstorms hazards in Shenzhen.

The model proposed in this research combines the variable fuzzy set theory with information diffusion method to solve the uncertainness of multiple hazards dynamic risk evaluation when data sets are incomplete. There are three parts needing to illustrate in the proposed model. Based on the definition of probabilistic risk, the proposed model takes time dimension into consideration to introduce the concept of dynamic probabilistic risk. Since the level of multiple hazards is affected by multiple indicators, the proposed model employs variable fuzzy set to calculate the relative membership degree and applies information entropy method to obtain the weights of criteria indicators for multiple hazards evaluation. Then the multiple indicators reduction model is introduced and can be used to get the comprehensive results of multiple hazards level degree. According to the concept of dynamic probabilistic risk which is charactered by insufficient data dimensions, the proposed model applies information diffusion method to estimate conditional

probability distribution and vulnerability curve with the comprehensive multiple hazards level, time data and multiple hazards losses. In the end, the proposed model calculates the expected value of conditional probability distribution and vulnerability curve to denote multiple hazards dynamic risk. This model deals with the multiple dimension indicators of different hazard and solves the problem of limited information in dynamic risk so as to improve the accuracy of risk evaluation results. The specific innovations made by the model are: (i) The model takes time dimension into consideration to introduce the concept of dynamic probabilistic risk. (ii) Considering that different kinds of hazards have different measurement indicators for the multiple hazards evaluation, a combination model of variable fuzzy sets and the information entropy method has been proposed. (iii) According to the concept of dynamic probabilistic risk which is charactered by insufficient data dimensions, the model applies information diffusion method to estimate conditional probability distribution and vulnerability curve. (iv) Finally, the model calculates the expected value of conditional probability distribution and vulnerability curve to denote multiple hazards dynamic probabilistic risk. To illustrate the proposed model, this research applies it to study typhoons and rainstorms hazards in Shenzhen.

Shenzhen locates in the southern China, a coastal city with low latitude, where the rainstorms and typhoons hazards have severely restricted the sustainable development of local economy and society. From 1990 to 2016, an average typhoon and rainstorm hazards have caused 3.4 deaths and affected 149000 people, and the average direct economic losses exceed 136 RMB millions. To assess the dynamic risk of typhoons and rainstorms hazards in Shenzhen area, this research collects the historical data about the maximum precipitation, strong wind intensity, and landing location from meteorological annual report and the typhoon website of China. According to the Classification Standards of Rainstorm and Typhoon hazards, this research uses the above data sets to obtain the multiple hazards level degree by converting the multiple hazards matrix into a single value. Combined with the multiple hazards level results, direct economic losses and time dimension, this research applies information diffusion method to estimate the conditional probability density and vulnerability curve of rainstorm and typhoon hazards. Ultimately, in accordance to the introduced concept of dynamic probabilistic risk, this research calculates the rainstorm and typhoon hazards dynamic probabilistic risk. The main results made by this research are: (i) The multiple hazards level degree can be classified into four types, and the probability of type II and III hazard occurrence is highest in August and September over the past 8 years.

This result shows that emergency management department should prepare corresponding emergency plans in advance to reduce the occurrence of secondary disasters in August and September. (ii) From the perspective of hazard losses, the direct economic losses caused by typhoons and rainstorms of the same hazard level in each month are different. The result indicates that the impacts of typhoon and rainstorm hazards on the economy are not same. Besides, for the same month, the influence of economic loss decreases gradually when the hazard level degree rises. This result indicates that the capacity of rainstorm and typhoon hazards resistance in Shenzhen is reliable, and the ability to cope with the sudden hazard is relatively strong under the existing emergence system. (iii) The risk value of typhoon and rainstorm hazards in each month is different and the highest hazard risk value occurs in August and September which brings 1.14 and 1.67 billion RMB economic losses respectively. From the above conclusions, it can be seen that these results are more in line with the actual situation and can give certain guidance of the emergency management in Shenzhen.

Keywords: dynamic risk evaluation, rainstorm hazard chain, variable fuzzy set theory, relative membership degree, information diffusion method

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Chapter 1 Introduction

1.1 Background

Risk analysis is an effective way to reduce the negative impacts of natural hazards and plays an increasingly important role in emergency management. It can not only guide the relevant decision makers to make correct emergency management decisions, but also reduce the negative impacts on society to certain extent. With the global climate change, many cities have suffered extreme natural hazards more frequently [1] and the trend of global climate change will put people's live under threat [2]. At the same time, human activities, such as the growth of settlements and the reduction of the area for natural hazard prevention, attribute to more severe adverse impacts of natural hazards [3]. Due to rapid urbanization, the modernization process of cities requires the government to make timely and effective emergency plans. Hence, it is important to assess the risk of natural hazards. Traditional methods of assessing risks mainly utilize Geographic Information System to get risk map, and information diffusion method to deal with incomplete data sets. However, there are few papers discussing dynamic risk of multiple hazards. Besides, in the existing study for dynamic risk evaluation, the collected data are limited with insufficient data dimensions. Since the current risk analysis cannot meet the requirement for emergency management, it is necessary to put forward more effective hazard chain risk assessment methods, or multiple hazards risk evaluation models.

The coastal cities of China are particularly vulnerable to typhoons, rainstorms and other meteorological phenomenon. It is unquestionable that typhoons and rainstorms hazards are the main natural hazards of China's coastal cities. Shenzhen locates in the southern China, a coastal city with a lower latitude, where the meteorological hazards have severely restricted the sustainable development of local economy and society. As China's first special economic zone, Shenzhen covers an area of 1996.85 km^2 and contains 10 districts, in which the urban areas lie on the east bank of the Zhujiang River and is surrounded by Daya Bay and Dapeng Bay. This geographic location shows that Shenzhen area may suffer from the rainstorm induced hazards more frequently and the hazards will put a constant risk to economic development, even the lives of human beings. For instance, the flooding induced by rainstorm hazard results in many people's death and injury, and severe economic losses for Shenzhen area [4]. According to the collected data, Shenzhen is particularly vulnerable to the hazards caused by typhoons and rainstorms. From 1990 to 2016, typhoon and rainstorm hazards have caused 3.4 deaths per time, affected 149000 people and the average direct economic losses exceed 136 RMB millions. It is very urgent to find mathematic models to eliminate the negative impacts caused by typhoons and rainstorms hazards for Shenzhen. However, there is very few paper to assess the natural hazards risk in a quantitative way [4]. And the meteorological factors, social factors and dynamic risk have not been considered in this paper. Besides, the meaning of risk evaluation result fails to be interpreted clearly. Considering the above-mentioned research gaps, this research proposes a brand-new model to evaluate multiple hazards dynamic risk and applies it to study typhoons and rainstorms hazards in Shenzhen.

1.2 Literature Review

Risk analysis appears often along with the randomness caused by multiple evaluation indicators, an abundance of unknown probability distributions, and the incomplete information contained in historical data sets. The basic goal of risk analysis is to model risk scenarios and find out some useful information. Researchers have done lots of work on modeling risk, here are the literature reviews on these aspects.

1.2.1 Definition of Risk

Since the 21st century, many researchers from domestic and abroad have conducted detailed studies on the concept of risk. Risk has been considered as the chance or probability that something happened and the value is affected by hazards level [5]. Compared with the different concepts of likelihood, probability and chance, the risk also has a variety of different interpretations. In this research, risk is defined as the scene which associates with some natural hazards characterized by fuzzy sets and is described by the probabilities that negative events will occur in the future. Huang [6] applied the integration value of probability density and vulnerable curve called expected probabilistic risk to describe the characters of natural hazard risk. Based on this definition, the risk could be classified into four categories: pseudo risk, probability risk, fuzzy risk, and uncertainty risk. Probabilistic risk describes the probability of some specific adverse scenario that may occur in the future and can be represented by probability model. There are many obstacles to solve probabilistic risk, such as the incompleteness information contained in historical data. So the fuzzy risk is introduced, which can solve the limited information problems contained in data sets by using fuzzy logic. But there are some limitations when confronting the multiple hazards events which characterized by fuzzy boundaries. Based on the two preceding risk definitions, this research proposes the improved probability risk, which is defined as the expected value risk of multiple adverse incident occurrence and there are some models which can be used to dynamically assess it when the data sets are incomplete. Then Eq. 1-1 can be used to calculate improved probabilistic risk.

$$Risk = \int probability\ distribution \cdot vulnerability\ curve\ d(factor). \tag{1-1}$$

1.2.2 Qualitative and Quantitative Risk Assessment

Risk has been defined as a measure of the severity of a hazard, or a measure of the probability of adverse effects. In order to evaluate the risk of natural hazards, it is necessary to build a reasonable and effective assessment system [7]. The risk assessment techniques can be classified into three main categories: the qualitative methods, the quantitative methods, and the hybrid techniques [8]. Since the evaluation result is composed of the probability of relevant hazard occurring and the severity of hazard losses, in the following contents, the quantitative and qualitative risk assessment methods have been summarized here.

Based on the experience of some experts, the risk can be assessed by analytical estimation processes, or assessed by means of several techniques such as geographic information systems (GIS). For example, Zhang et al. analyzed the four aspects of flood hazards from multiple indicators by combining Analytical Hierarchy Process (AHP) and Geographic Information System (GIS), and obtained the comprehensive weighted risk assessment value [9]. Chen et al. [10] provided useful detailed information for flood risk management by combining with AHP and GIS in flood risk assessment. Rakwatin et al. used synthetic aperture radar (SAR) imagery and optical satellite imagery to map the flooding area, so as to estimate the flood risk in real time [11]. Based on the results obtained in these papers, it can be found that only when the amount of data is sufficient, the effective risk assessment results can be obtained. Aye et al. provided a prototype of an interactive web-GIS tool for the risk evaluation and management evaluation in Central East Moldavian

Region, considering the occurrence of floods and earthquakes [12]. Although GIS assessment technology can provide real-time hazards risk maps [13], there is an unavoidable fact that GIS adopted to risk evaluation can not be quantified with insufficient data sets.

The risk also can be considered as a quantity and measured in a quantitative way which is expressed by a mathematical model by the use of real data. Naturally, the holistic approach for risk assessment is better than a non-holistic approach. Huang put forward the concept about probabilistic risk, which can be quantified as the expected value to predict future risk based on historical data [14]. Based on this concept, Huang et al. [15] estimated the probability distribution and the vulnerability curve to obtain the expected risk, which not only calculated the occurrence likelihood of a specific event but also considered the severity of outcome. Van Dyck et al. [16] developed the probabilistic model to estimate the rate of flood-induced losses over a large geographical region. Abebe et al. [17] put forward the Bayesian belief network model to evaluate the flood vulnerability curve of urban areas and then quantify the flooding risk. Ribeiro et al. [18] proposed a probabilistic model, based on a bivariate copula approach using elliptical copulas, to estimate the probability of economic losses. From the above studies, the calculation of probabilistic risk is determined by meteorological factors and social factors, and this research will assess the multiple hazards risk by using probabilistic risk.

1.2.3 Quantitative Risk Modeling

Based on the definition of probabilistic risk, there are many interpretations about risk evaluation result. Besides, assessing the risk quantitatively is a challenging task because of the randomness caused by multiple evaluation factors, unknown probability distributions, and the incompleteness information contained in data sets. To solve these problems, the traditional regression model, variable fuzzy sets and information diffusion method have been introduced.

1.2.3.1 Single Quantitative Risk Modeling

The most important part of regression model is to estimate the hypothetical probability distribution parameters based on large amount of data. Cai et al. proposed quantile function model, which combined the regression model with Monte-Carlo framework to estimate probabilities risk of flood event [19]. For the big enough dataset, Eghbali et al. presented a new hybrid clustering model based on artificial neural networks and genetic algorithms to calculate the flood risk by estimating the maximum water volume of flood [20]. This type of model is a pure experience summary and the tools used are greatly restricted by the reasonable hypothetical probability distributions. And traditional probability statistical methods ignore the fuzziness of risk assessment with incomplete data sets and require a large sample size of data. To solve the risk assessment problem where the randomness and ambiguity are inherent in the multiple hazards data sets, Shen et al. [21] coped with the criminal risk by using fuzzy random theory to verify the losses probability. Ke et al. constructed the assessment model based on the variable fuzzy model to deal with the uncertainty and ambiguity of the seawater risk assessment [22]. Carreno et al. [23] applied the fuzzy sets theory into the seismic risk evaluation when the data are not available and insufficient. Wang et al. proposed a combined model to overcome the limitations of traditional evaluation methods which only uses the point value instead of an interval to assess the quality of river water [24]. These studies have successfully applied the fuzzy theory to quantify probabilistic risk, and therefore it has potential to improve the accuracy of risk assessment results. On the other hand, some researchers have focused on information diffusion method, which belongs to fuzzy sets theory, to represent the probabilistic risk when the data is incomplete. Huang [25] gave the definition of fuzzy risk and applied a fuzzy average algorithm to update fuzzy risk based on information diffusion method. There are some studies of assessing flood risk involving meteorological factors and social factors. For instance, the flood risk assessment model based on information diffusion method is used to deal with the small sample size [15, 26]. Honestly, these methods could solve one of the problems in assessing probabilistic risk, but the results may not be so reliable.

1.2.3.2 Improved Quantitative Risk Modeling

There are some drawbacks in these methods. For instance, it is difficult to find the true relationships and the randomness of risk assessment with incomplete data has also been ignored. Hence, taking the strengths of above studies both into consideration, it can combine the advantages of different methods to construct a new approach to improving the accuracy of assessment result. For example, taking randomness caused by inherent stochastic variability of sample sets and the limited knowledge from incomplete data sets into consideration, Li put forward the improved model [7] to assess flood risk and the back-propagation neural network model [27] to transfer the multiple dimension evaluation factors into a single value so as to enhance the precision of probability estimation. The result shows that this integrated model can improve the reliability of single hazards risk evaluation. Chen proposed another model focused on agricultural drought risk assessment model, which used the information diffusion method to calculate the risk level classification criteria, and then used the variable fuzzy set to assess the sensitivity and vulnerability of drought risk [28]. The risk evaluation result is determined by some index which is not better than expected probabilistic risk. So, AHMADI et al. [29] proposed a new algorithm based on variable fuzzy set and information diffusion method to deal with diabetes risk assessment with incomplete data sets and produced more accurate results with fewer errors. Besides, there are many other improved models, such as the diffused interior-outer-set model to analyze the flood risk dynamically when the sample sets are incomplete [30], the projection pursuit method optimized by immune evolutionary algorithm to assess the risk of drought [31] and the comprehensive risk assessment problem with various indexes being solved by Cloud-based information diffusion and Analytic Hierarchy Process (CID-AHP) model [32]. From above studies, the risk assessment of single hazard has been studied thoroughly, but the multiple hazards dynamic probabilistic risk have not been considered.

1.2.4 Existing Problems of Risk Assessment

There are many approaches to assessing risk, such as utilizing Geographic Information System to get risk map and applying information diffusion method to deal with incomplete data sets, but a general methodology is lack of assessing the multiple hazards dynamic risk when the sample sets are incomplete. Some papers introduced the definitions of dynamic risk and assessed the multiple hazards risk [33–35], but there are few papers discussing the uncertainty of multiple hazards and considering dynamic risk under time dimension. Since the multiple hazards level will be affected by multiple indicators, the hazard results are often uncertain. Besides, in the existing study for dynamic risk evaluation, the collected data are limited with insufficient data dimensions. These problems are actually new issue, which is called multiple hazards dynamic risk evaluation. Considering the multiple hazards risk evaluation contains fuzzy concept with multiple indicators and classes, the variable fuzzy sets theory introduced by Chen [36] has given the relative membership degree to evaluate the fuzzy concept. Dynamic probability risk has been proposed by Huang [37], who puts forward the concept about dynamic risk and estimates the conditional probability and vulnerability curve by using normal information diffusion estimator. From the above researches, risk evaluation is a very important issue in emergency management, but there are few papers focusing on building mathematic models to predict multiple hazards dynamic risk when data sets are incomplete. Considering the above-mentioned research gaps, this research proposes a brand-new model to evaluate multiple hazards dynamic risk and applies it to study typhoons and rainstorms hazards in Shenzhen.

1.3 Research Aims and Objectives

Due to rapid urbanization, the development of society urgently needs more effective hazard chain risk assessment methods, or multiple hazards risk evaluation models, especially under the circumstance of climate change. There are many models to assess hazard risk and different researchers have different understanding towards risk. Traditional methods of assessing risks mainly utilize Geographic Information System to get risk map, and information diffusion method to deal with incomplete data sets. However, there are few papers discussing the uncertainty of multiple hazards and considering dynamic risk under time dimension. Besides, in the existing study for dynamic risk, the collected data are limited with insufficient data dimensions. In view of the shortcomings about risk assessment, this research takes time dimension into consideration to introduce the concept of dynamic probabilistic risk and proposes the variable fuzzy set and information diffusion method model to assess multiple hazards dynamic probabilistic risk.

The model proposed in this research combines the variable fuzzy set theory with information diffusion method to solve the uncertainness of multiple hazards dynamic risk evaluation when data sets are incomplete. More specifically, the proposed model outlines how relative membership degree functions can be used to obtain the comprehensive hazard level degree, while applying the information entropy method to obtain the weights of criteria indicators. Based on the concept of dynamic probabilistic risk, information diffusion method can be applied to estimate conditional probability distribution and vulnerability curve, by synthesizing the comprehensive hazard level degree, time data and hazard losses. Then the expected value of multiple hazards dynamic risk can be calculated by using the normal information diffusion estimator so as to improve the accuracy of risk evaluation results. To illustrate the proposed model, this research applies the model to assess the rainstorms and typhoons hazards dynamic risk in Shenzhen area. Based on the historical data about the maximum precipitation, strong wind intensity, and landing location when these hazards occurred, the proposed model uses the above data sets to obtain the comprehensively hazard level degree by using variable fuzzy sets and information entropy theory. Considering the comprehensive hazard level degree, direct economic loss and time dimension, the proposed model estimates the conditional probability density and vulnerability curve of rainstorm and typhoon hazards. By the definition of dynamic probabilistic risk, the proposed model calculates the rainstorm and typhoon hazards dynamic probability risk to guide the emergency management in this area.

1.4 Contributions

In this research, the variable fuzzy set and information diffusion dynamic risk assessment model has been proposed and the case study based on the maximum precipitation, strong wind intensity, landing location of typhoon and direct economic losses has been discussed. The innovation points of this research are: (1) Based on the definition of probabilistic risk, this research takes time dimension into consideration to introduce the improved dynamic probabilistic risk. (2) Considering the evaluation of multiple hazards degree, this research proposes a combination model of variable fuzzy sets and information entropy method to convert the multiple dimension indicators of different hazard into a single degree value so as to improve the accuracy of hazard level degree. (3) Based on the definition of dynamic probabilistic risk, this research applies information diffusion method to estimate condition probability distribution and vulnerability curve by using the obtained multiple hazards degree value, time data and hazard losses. (4) This research calculates the expected value of condition probability distribution and vulnerability curve to denote multiple hazards dynamic probabilistic risk. (5) To illustrate the proposed model, this research applies it to study typhoons and rainstorms hazards in Shenzhen and the results show: (i) August has the highest probability of hazard occurrence and the probability of type II and III hazard level occurrence is highest in August and September over the past 8 years. (ii) From the perspective of hazard losses, the direct economic losses caused by typhoon and rainstorm of the same hazard level degree in each month are different. (iii) The risk value of typhoon and rainstorm hazards in each month is different and the highest hazard risk value occurs in August and September which bring the greatest economic losses at 1.14 and 1.67 billion RMB respectively. From the above conclusions, it can be seen that these results are more in line with the actual situation and can give certain guidance of the emergency management in Shenzhen.

1.5 Structure of Thesis

This thesis consists of six chapters, the introduction chapter will show the whole idea of the research project. Then the variable fuzzy sets (VFS) theory and information entropy method (IEM) will be given in chapter two, and the VFS-IEM model based on variable fuzzy sets and information entropy method has also been presented. In chapter three, the information diffusion method is introduced. We will give some definitions and one principle to ensure this method can eliminate the fuzziness in integrated probability risk evaluation and improve the estimation accuracy. Combining with the multiple hazards level which can be obtained by VFS-IEM model, chapter four uses variable fuzzy sets and information diffusion method (VFS-IDM) model to evaluate integrated dynamic probability risk. The VFS-IDM model takes time dimension into consideration and uses the information diffusion method to extract as much useful underlying information as possible from data sample sets to estimate the conditional probability density of hazard occurrence and vulnerability curve. In the end, chapter five will give a case study about Shenzhen city to verify the model and chapter six will make some conclusions and illustrate future works.

Chapter 2 Variable Fuzzy Set Dimension Reduction Model

The risk assessment problems always contain the randomness and fuzziness. Considering that the multiple hazards risk is a fuzzy concept with multiple indicators and classes, are there any methods to solve this kind of problem? In this chapter, the variable fuzzy set dimension reduction model is given to deal with this problem. Some researches based on variable fuzzy sets theory, introduced by Chen [36], have shown that the relative membership function can be used to evaluate the fuzzy concept. For example, Li proposed the fuzzy comprehensive evaluation method to solve the flood risk assessment problems with fuzziness boundaries [38] and Beaula et al. used variable fuzzy sets to calculate the synthetic disaster degree of Nagapattinam district under north-east monsoon rainfall's incomplete data sets [39]. This chapter uses variable fuzzy sets theory (VFST) to realize the dimension reduction of multiple hazards data and to eliminate both randomness and fuzziness in risk assessment. To be more specific, this chapter will put forward the variable fuzzy set dimension reduction model to convert the indicator intervals of the multiple hazards sample sets into a single degree value and get the processed data which has eliminated both randomness and fuzziness of multiple hazards risk assessment.

2.1 Variable Fuzzy Sets Theory

Variable fuzzy sets theory (VFST), which deals with randomness and fuzziness, may provide an appropriate tool for solving the multiple hazards risk assessment. For example, the relative membership degree methods integrate multiple factors for quantify the multiple hazards risk assessment comprehensively. The VFST is the extension of fuzzy sets theory which has been proposed by Zadah [40]. However, if the variability of measurement standard is not considered, the result will be static. Therefore, the concept of VFS proposed by Chen, which is based on the fuzzy sets and relative difference function, has promoted the development of fuzzy sets theory.

2.1.1 Definition of Variable Fuzzy Sets

In order to define the concept of variable fuzzy sets (VFS), we can get the detailed results of variable fuzzy sets theory which is introduced by Chen [36]. For a fuzzy set U and the random element $u \in U$, the mapping D denoted by $D(u)$ can be used to split opposite concept U into Variable Fuzzy Sets (VFS) by transferring the fuzzy set U into real value.

$$u \in U \longmapsto D(u) \in [-1, 1].$$

For any elements u ($u \in U$), the relative membership degree functions (RMDFs) $\mu_A(u)$ and $\mu_A^c(u)$ express the extent of accept (A) and reject (A^c) respectively.

$$\mu_A(u) + \mu_A^c(u) = 1 \qquad \mu_A(u), \mu_A^c(u) \in [0, 1]. \tag{2-1}$$

Then, based on the mapping $D(u)$, a new function can be defined to figure out the expression of RMDFs.

$$D_A(u) = \mu_A(u) - \mu_A^c(u) \qquad D_A(u) \in [-1, 1],$$

where $D_A(u)$ is called relative difference degree of u to A. Based on Eq. 2-1, the expression of RMDF can be calculated by

$$\mu_A(u) = [1 + D_A(u)]/2. \tag{2-2}$$

Now the fuzzy set U can be shown as following three parts, let

$$V = \{(u, D)|u \in U, D_A(u) = \mu_A(u) - \mu_A^c(u), D \in [-1, 1]\}. \tag{2-3}$$

$$A_+ = \{u|u \in U, \mu_A(u) > \mu_A^c(u)\},$$

$$A_- = \{u|u \in U, \mu_A(u) < \mu_A^c(u)\},$$

$$A_0 = \{u|u \in U, \mu_A(u) = \mu_A^c(u)\}.$$

Here V is just defined as Variable Fuzzy Sets (VFS) of U, and A_+, A_-, A_0 are called the attracting sets, repelling sets, and balance boundaries of VFS V, respectively.

2.1.2 Induction of Relative Membership Degree Function

Based on the definition of VFS, we know the relative difference degree function $D_A(u)$ has shown the difference of membership degree. That is, when the relative difference degree(RMD) $\mu_A(u)$ is larger than $\mu_A^c(u)$, the major property of u is acceptable, and the minor property is exclusion. So the ratio can be used to represent this relationship in the interval and then find out the expression of RMDFs. In other words, the ratio could calculate the relative membership degree for class interval $u \in U$ when a sample point x is given. The following content has given the process of Relative Membership Degree Function induction:

For fixed $u \in U$, we define the interval X_0 = [a, b] as the attracting sets of VFS V on the real axis, i.e. the interval X_0 satisfy $\mu_A(u) > \mu_A^c(u)$. Then define X is a certain extended interval [c, d] including X_0, i.e. $X_0 \subset X$, besides, taken the point M satisfy $\mu_A(u) = 1$. For any sample point x which is coordinated with fuzzy set $u \in U$ and called the observation value of the u class, the Fig. 2-1 has shown the relationship between the above points.

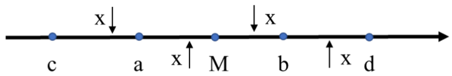

Figure 2-1 The linear relationship between different position point x, M and zone [a, b], [c, d]

According to the definition of VFS, interval [c, a] and [b, d] are the rejection sets with respect to class internal u, i.e. interval of $\mu_A(u) < \mu_A^c(u)$. So for the different position of point x, the different result of relative membership degree $\mu_A(u)$ can be calculated by the following ratio equation. Before that, the problem of how to calculate the parameter M must be solved.

Thanks to the research of how to define the balance boundaries of VFS [41], we can get the important parameter M_{rl} by following equation.

$$M_{rl} = \frac{L-l}{L-1}a_{rl} + \frac{l-1}{L-1}b_{rl}. \tag{2-4}$$

where r stands for the assessment indicator set, $r = 1, 2, \ldots, R$, l denotes the assessment class interval, $l = 1, 2, \ldots, L$. $M = (M_{rl})$ is the reference for determining RMDF according to different location of x. Eq. 2-4 satisfies following suppositions: (i) when $l = 1$, then $M_{r1} = a_{r1}$; (ii) when $l = L$, then $M_{rL} = b_{rL}$; (iii) when $l = \frac{L+1}{2}$, then $M_{rl} = \frac{a_{rL}+b_{rL}}{2}$.

Assume the point $M = (M_{rl})$ satisfies suppositions (iii) and $D_A(u) = 1$ in the attracting set [a, b]. For any observation value of the u class and sample point x, the relative difference membership degree can be replaced by a ratio. Here is the details:

- When x locates in the left of parameter M (Fig. 2-2), the relative difference degree can be calculated by Eq. 2-5.

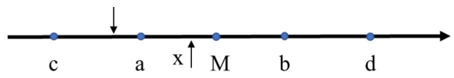

Figure 2-2 x locates in the left position of parameter M

$$\begin{cases} D_A(u) = \left(\frac{x-a}{M-a}\right)^p & x \in [a, M] \\ D_A(u) = -\left(\frac{x-a}{c-a}\right)^p & x \in [c, a] \end{cases}, \tag{2-5}$$

where p is hyper-parameter and the function can be proved that corresponds to the definition of $D_A(u)$. Combining with Eqs.2-2 and 2-5, we have the expression of RMDF:

$$\begin{cases} \mu_A(u) = 0.5[1 + \left(\frac{x-a}{M-a}\right)^p] & x \in [a, M] \\ \mu_A(u) = 0.5[1 - \left(\frac{x-a}{c-a}\right)^p] & x \in [c, a] \end{cases}. \tag{2-6}$$

- When x locates in the right of M (Fig. 2-3), the relative difference degree can be calculated by Eq. 2-7

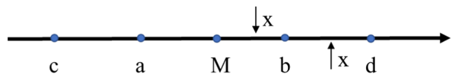

Figure 2-3 x is locates in the right position of parameter M

$$\begin{cases} D_A(u) = \left(\frac{x-b}{M-b}\right)^p & x \in [M, b] \\ D_A(u) = -\left(\frac{x-b}{d-b}\right)^p & x \in [b, d] \end{cases}. \tag{2-7}$$

Combining with Eqs.2-2 and 2-7, the RMDF can be denoted as

$$\begin{cases} \mu_A(u) = 0.5[1 + \left(\frac{x-b}{M-b}\right)^p] & x \in [M, b] \\ \mu_A(u) = 0.5[1 - \left(\frac{x-b}{d-b}\right)^p] & x \in [b, d] \end{cases}. \tag{2-8}$$

From the above Equations, it can be determined that the RMDF is affected by hyper-parameter p and the position between random point x with parameters a, b, c, d, and M. The following conditions are RMDF should satisfy: (i) when $x \notin [c, d]$ or $x = c, x = d$, then $\mu_A(u) = 0$; (ii) when $x = a, x = b$, then $\mu_A(u) = 0.5$; (iii) when $x = M$, then $\mu_A(u) = 1$. In general, we take $p = 1$ such that the Eqs. 2-5 and 2-7 become linear functions.

However, the above mentioned process of membership calculation is very cumbersome. We need judge the position relationship between random point x and other parameters constantly and it is difficult to quickly obtain the RMD matrix of each sample. To solve that, there may be some characteristic for different location of random point x

with respect to the class interval u. By some inductions, the significant point is that the calculation of relative membership degree can be classified into two types [42]. When the random point x locates in the lowest or highest grade of the class interval, the RMD sum of this and adjacent interval levels is equal to 1, and when random point x locates in the interval of the mid-level, the RMD sum of its adjacent interval levels is 0.5. The result will be given in the following content, without loss of generality, we only consider one of the indicator set $u_{1l}, l = 1, 2, \ldots, L$.

- When the random point x locates in the lowest grade of the class interval, the position between the random point x with parameters a_{1l}, b_{1l}, c_{1l}, d_{1l} and M_{1l} can be depicted as Fig. 2-4. The relative membership degree can be calculated by Eqs. 2-6 and

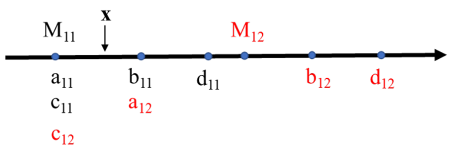

Figure 2-4 The position between the random point x with parameter M_{1l} and zones $[a_{1l}, b_{1l}]$, $[c_{1l}, d_{1l}]$

2-8 and has the following characteristics.

$$\begin{cases} \mu_A(u)_1 = [\mu_A(u)_{11} \quad \mu_A(u)_{12} \quad 0 \quad \cdots \quad 0] \\ \mu_A(u)_{11} + \mu_A(u)_{12} = 1 \\ 0.5 \leq \mu_A(u)_{11} \leq 1 \\ 0 \leq \mu_A(u)_{12} \leq 0.5 \end{cases} . \tag{2-9}$$

- Same as the lowest grade of the class interval, when x locates in the highest grade of the class interval (Fig. 2-5), the relative difference degree matrix can be calculated by Eq. 2-10.

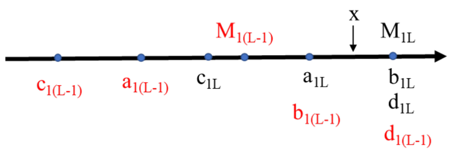

Figure 2-5 The parameters' position of the class interval highest grade

$$\begin{cases} \mu_A(u)_1 = [0 \quad \cdots \quad 0 \quad \mu_A(u)_{1(L-1)} \quad \mu_A(u)_{1L}] \\ \mu_A(u)_{1(L-1)} + \mu_A(u)_{1L} = 1 \\ 0.5 \le \mu_A(u)_{1L} \le 1 \\ 0 \le \mu_A(u)_{1(L-1)} \le 0.5 \end{cases} . \tag{2-10}$$

- When the random point x locates in the interval of a mid-level, the position between random point x with parameters a_{1l}, b_{1l}, c_{1l}, d_{1l} and M_{1l} can be depicted as Fig. 2-6. And the characteristics of relative membership degree matrix can be described by

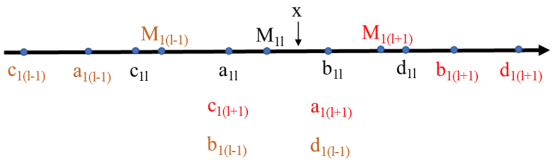

Figure 2-6 The position between the random point x with parameter M_{1l} and zones $[a_{1l}, b_{1l}]$, $[c_{1l}, d_{1l}]$

Eq. 2-11.

$$\begin{cases} \mu_A(u)_1 = [0 \quad \cdots \quad 0 \quad \mu_A(u)_{1(l-1)} \quad \mu_A(u)_{1l} \quad \mu_A(u)_{1(l+1)} \quad 0 \quad \cdots \quad 0] \\ \mu_A(u)_{1(l-1)} + \mu_A(u)_{1(l+1)} = 0.5 \\ 0 \le \mu_A(u)_{1(l-1)} \le 0.5 \\ 0 \le \mu_A(u)_{1(l+1)} \le 0.5 \end{cases} . \tag{2-11}$$

The RMD calculation method can make the problem more easier and find out the RMD value by less processing of RMDF calculation [42], we will apply this method into our model to assure the accuracy of RMD value.

2.2 Information Entropy Method to Decide the Indicator Weights

The fuzzy comprehensive evaluation method is a process of comprehensive evaluation using fuzzy set theory and weight coefficients, and the result can reflect the comprehensive result of the evaluation problem. So some problems should to be solved, such as how to find the weight of indicators which plays a very important role in fuzzy comprehensive evaluation model. In general, weight is determined by a ratio of indicators value at each monitoring point over a corresponding standard. However, it is difficult to calculate the weight of multiple hazards indicator, so many papers used subjective methods to determine the weight of indicators, such as Analytic Hierarchy Process (AHP) method [33]. For the purpose of making the assessment results more reliable, we must find other methods to find the weights. By the study from Qiu, the information entropy can be used to solve this problem. Methods holds for that the entropy coefficients can measure the importance of criteria index. The study shows when the information entropy of a certain evaluation index is large, it indicates that this index has little influence on the comprehensive result, so the evaluation index should have a smaller weight, and vice versa [43].

In the following section, the information entropy method (IEM) [44] is used to solve the comprehensive evaluation problem. For each elements in $U = (u_{rl})$, we define the element u_{rl} as measured value from lth object for rth indicator and give the final result by following formulas.

$$f_{rl} = u_{rl}/\sum_{l=1}^{L} u_{rl} \qquad h_r = \frac{-1}{lnL} \cdot \sum_{l=1}^{L} (f_{rl} ln f_{rl}), \tag{2-12}$$

where the regularization membership vector f_{rl} denotes the frequency value of lth evaluating object criteria and supposing $f_{rl} ln f_{rl} = 0$ if $f_{rl} = 0, r = 1, 2, \ldots, R, l = 1, 2, \ldots, L$. Then the entropy coefficient of indicators can be defined as

$$\omega_r = (1 - h_r)/(R - \sum_{r=1}^{R} h_r). \tag{2-13}$$

where the result ω_r is the entropy coefficient of rth indicator.

2.3 VFS-IEM Comprehensive Evaluation Model

The multiple hazards risk assessment is a fuzzy concept with multiple indicators and classes. For each sample x, the measured value from rth indicator to lth class can be denoted as relative membership degree matrix $\mu_A(u)$ by using RMDF. Because the subjectivity of determining indicator weight and assessment standard in fuzzy sets, the comprehensive evaluation results are often incompatible, even make unreliable conclusions. To assess the fuzzy sets more reliable, we should also find out the relative membership degree of fixed sample point x to each class in a reasonable way and then calculate the comprehensive value of fuzzy assessment interval. This section proposes the variable fuzzy set and information entropy method (VFS-IEM) model to solve the multiple hazards risk evaluation problem and the following content is the induction process.

The relative membership degree of indicator rth with respect to lth class can be expressed as generalized weighted distance d_{al} and d_{bl}, respectively [41].

$$d_{al} = \{\sum_{r=1}^{R}[\omega_r(1-\mu_A(u)_{rl})]^{\alpha}\}^{\frac{1}{\alpha}}, \tag{2-14}$$

$$d_{bl} = \{\sum_{r=1}^{R}[\omega_r(1-\mu_A^c(u)_{rl})]^{\alpha}\}^{\frac{1}{\alpha}}. \tag{2-15}$$

and α is distance hyper-parameter. When $\alpha = 1$, it is named as the Hamming Distance. When $\alpha = 2$, it is named as the Euclidean distance. Based on those definition, we define $\nu_A(u)_l$ as the relative membership degree of fixed sample point x to lth class and the result remains to be determined.

Then let the value of $\nu_A(u)_l$ and $\nu_A^c(u)_l$ as the weight factors with respect to the generalized weighted distance D_a and D_r , the relationship can be defined as the following equations

$$D_a = \nu_A(u)_l \cdot d_{al} \qquad D_r = \nu_A^c(u)_l \cdot d_{bl} = (1-\nu_A(u)_l) \cdot d_{bl}. \tag{2-16}$$

To find out the expression of $\nu_A(u)_l$, we need to minimize the error between D_a and D_r.

Constructing the error function F, we can apply the quadratic form error function [41] to denote as F.

$$minF(\nu_A(u)_l) = (\nu_A(u)_l)^2 \cdot d^{\beta}{}_{al} + (1-\nu_A(u)_l)^2 \cdot d^{\beta}{}_{bl}, \tag{2-17}$$

and β is the optimization hyper-parameter. This model can be classified into two different types, $\beta = 1$ denotes the least single method and $\beta = 2$ is the least square method.

By differentiating Eq. 2-17 with $\nu_A(u)_l$ and equating it to zero, we can get the expression of relative membership degree of fixed sample point x to lth class. That is

$$\frac{dF(\nu_A(u)_l)}{d\nu_A(u)_l} = 0. \tag{2-18}$$

Eq. 2-18 becomes

$$\nu_A(u)_l = \frac{d^{\beta}{}_{bl}}{d^{\beta}{}_{al} + d^{\beta}{}_{bl}} = (1 + (\frac{\sum_{r=1}^{R}[\omega_r(1-\mu_A(u)_{rl})]^{\alpha}}{\sum_{r=1}^{R}[\omega_r\mu_A(u)_{rl}]^{\alpha}})^{\frac{\beta}{\alpha}})^{-1}. \tag{2-19}$$

The maximum principle tells us the result $\nu_A(u)_l$, defined by Eq.2-19, is the relative membership degree of sample point x to lth class. Then make normalization processing on that result, we can get the regularization comprehensive relative membership vector for each sample.

$$U = (\nu_A^o(u)_l) \qquad \sum_{l=1}^{L}\nu_A^o(u)_l = 1, \tag{2-20}$$

where

$$\nu_A^o(u)_l = \frac{\nu_A(u)_l}{\sum_{l=1}^{L} \nu_A(u)_l}. \tag{2-21}$$

From the above induction, we say that the problem of multiple hazards risk assessment can be assessed by VFS-IEM comprehensive evaluation model (2-22) which can be summarized in Fig. 2-7. The result shows that each sample point has been converted from multiple dimension indicator into a single degree value so as to make comprehensive evaluation results more reliable.

$$\begin{cases} \nu_A(u)_l = [1 + (\frac{\sum_{r=1}^{R}[\omega_r(1-\mu_A(u)_{rl})]^\alpha}{\sum_{r=1}^{R}[\omega_r \mu_A(u)_{rl}]^\alpha})^{\frac{\beta}{\alpha}}]^{-1} \\ \omega_r = (1-h_r)/(R - \sum_{r=1}^{R} h_r) \\ \nu_A^o(u)_l = \frac{\nu_A(u)_l}{\sum_{l=1}^{L} \nu_A(u)_l} \\ H = (1 \quad 2 \ldots L) \cdot (\nu_A^o(u)_l)^T \end{cases}. \tag{2-22}$$

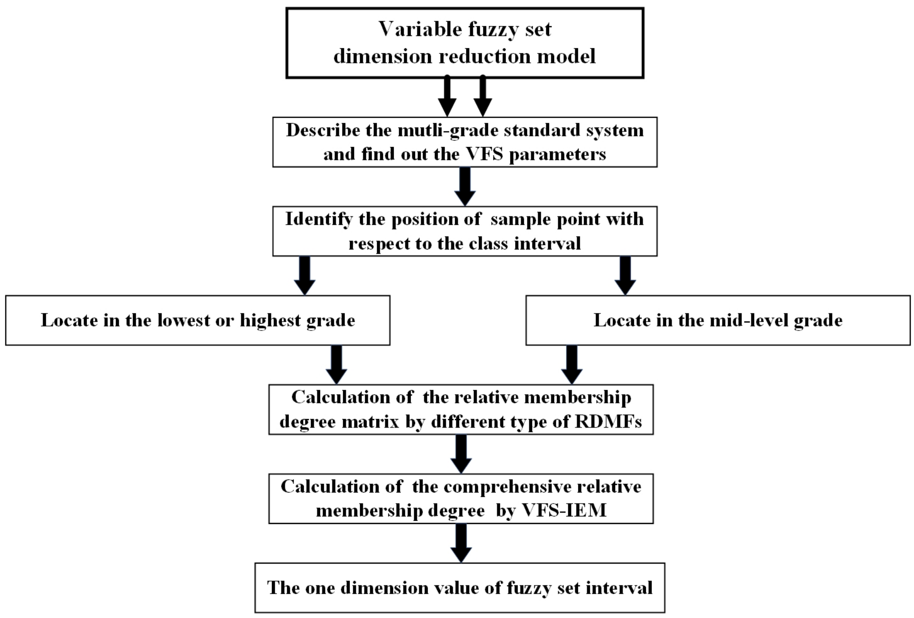

Figure 2-7 Flow chart of the VFS-IEM comprehensive evaluation model

2.4 Brief Summary

This chapter addresses the multiple hazards risk assessment problem which is characterized by a fuzzy concept with multiple indicators and classes. The variable fuzzy set dimension reduction model has been proposed, which can be used to deal with the fuzzy concept evaluation problem by combining relative membership function with information entropy method. This comprehensive evaluation model converts the multiple dimension indicators of each sample into a single degree value to eliminates the border effect on assessment result and minimizes the estimation standard error. Furthermore, the proposed model can make full use of the information contained in the data sets to deal with the risk assessment problem. For multiple hazards risk evaluation problem, we can apply the VFS-IEM comprehensive evaluation model to deal with the fuzzy concept and then simplify the evaluation problem.

Chapter 3 Information Diffusion Method

Generally, data can reflect the facts about real world and statistical model can find the information or patterns behind the data sets. However, in many cases, it is difficult to collect multiple hazards data sets, and the information carried by historical data is incomplete. So the estimated result is very unreliable by using statistical model when the data sets are incomplete. To solve this problem, the information diffusion method (IDM), which belongs to fuzzy sets theory, is introduced. Many papers have showed the capability of information diffusion method to deal with incomplete data sets. For example, the flood risk assessment model based on information diffusion method has been proposed to deal with the incomplete data sets [6, 26, 45]. This chapter will introduce information diffusion method and apply it to assess dynamic integrated probability risk.

The researches by Huang [46, 47] have given many results about information diffusion method (IDM). To estimate the relationship between data sets when the data sets are incomplete, the information diffusion method can be used to improve the estimation accuracy of density function and the input-output relationship. In the following content, this chapter will give the fundamental theory with respect to information diffusion method and prove that normal information diffusion estimator is better than non-diffusion estimator to estimate the relationships between incomplete data sets.

3.1 Fundamental Definition

Definition 1 Suppose $X = x_1, x_2, \ldots, x_m$ is a random given sample set, $U = u_1, u_2, \ldots, u_m$ is the universal field, where m denotes the dimension of sample. The information diffusion method is a mapping μ: $X \times U \to [0,1]$ that satisfies the following three conditions [47]:

(1) $\forall x \in X$, let $\hat{u}$ be the observed value of x, then $\mu(x,\hat{u}) = \max\limits_{u \in U} \mu(x,u)$.

(2) $\forall\, x \in X, \forall\, u^{'}, u^{''} \in U$, if $\|u^{'} - x\| \leq \|u^{''} - x\|$, then $\mu(x,u^{'}) \geq \mu(x,u^{''})$.

(3) $\forall x \in X$, $\int_U \mu(x,u)du = 1$. If V is discrete, then $\sum_U \mu(x,u) = 1$. Where μ denotes as the *diffusion function* and U as the *monitoring space*. □

Using the diffusion function $\mu(x,u)$, the given sample X can be diffused into the fuzzy set $D(X) = \{\mu(x,u) | x \in X, u \in U\}$. By doing that, the information contained in incomplete samples can be used to estimate the probability density or the fuzzy relationship between data sets without knowing what distribution the data sets satisfies. For any fixed diffusion function to deal with the sample of estimating the density or fuzzy relationship, the corresponding result is called the *diffusion estimator*. The following contents will give the fundamental definitions.

Definition 2 Let $X = \{x_i | i = 1, 2, \ldots, n\}$ be one dimensional random sample, $U = \{u_j | j = 1, 2, \ldots, J\}$ is the universal field. $\forall x_i \in X$, we calculate the normal diffusion for the sample x_i to diffuse to monitoring point u_j by Eq. 3-1.

$$\mu_{(1)}(x_i, u_j) = exp[-\frac{(x_i - u_j)^2}{2h^2}], \quad x_i \in X, u_j \in U. \tag{3-1}$$

By the study of Huang [47], the *diffusion coefficient* can be calculated by Eq. 3-2.

$$h = \begin{cases} 0.6841(b-a), & for \quad n = 5; \\ 0.5404(b-a), & for \quad n = 6; \\ 0.4482(b-a), & for \quad n = 7; \\ 0.3839(b-a), & for \quad n = 8; \\ 2.6581(b-a)/(n-1), & for \quad n \geq 9. \end{cases} \tag{3-2}$$

$$where \quad b = \max_{1 \leq i \leq n}\{x_i\}, \quad a = \min_{1 \leq i \leq n}\{x_i\}.$$

Then the *normal diffusion function* defined by Eqs. 3-1 and 3-2 diffuses the information carried by observation x_i to the monitoring point u_j in a normal way. Furthermore, we have the *n − dimension diffusion fuction* of X on V.

$$\mu(x_i, V) = \prod_{l=1}^{n} \mu_{(l)}(x_{li}, v_{lj}). \tag{3-3}$$

□

Definition 3 For estimating the probability density, we use p_{ij} to denote the value of $\mu(x_i, u_j)$ called the *provided information*. The matrix means that the sample point x_i diffuses information, valued p_{ij}, to the monitoring point u_j. For estimating the relationship between samples, let a sample point with input x_i and output y_i, the universal field $(U, V) = \{(u_j, v_k) | j = 1, 2, \ldots, J; k = 1, 2, \ldots, K\}$ and normal diffusion function μ, we use d_{ijk} to denote the value of $\mu_{(u_j \cdot v_k)}(x_i, y_i)$ called the *diffused information*, which means that sample point (x_i, y_i) diffuses information, obtained d_{ijk}, to the monitoring point (u_j, v_k). □

Definition 4 Let $X = \{x_i | i = 1, 2, \ldots, n\}$ be the data sets drawn from the unknown population with probability density function $p(x)$. Given J intervals $I_1, I_2, \cdots, I_J$ with width

Δ and u_j is the corresponding monitoring point. By Def. 3, the *provided information* $\mu(x_i, u_j)$ can be used to estimate the density function [48]. So $p_n(x)$

$$p_n(x) = \frac{1}{n\Delta}\sum_{i=1}^{n}\mu(x_i, u_j),$$

is called the *information diffusion estimator* about $p(x)$. □

Definition 5 By Def. 3, we define the matrix $Q = (q_{jk})$, where $q_{jk} = \sum_{i=1}^{n} d_{ijk}$, as *primary information matrix* of X on (U, V).

Let

$$s_k = \max_{1 \le j \le J} q_{jk}, \quad k = 1,\ 2, \cdots,\ K;$$

Then based on Q, each element v_k of V can be represented by a fuzzy set μ_k.

$$\mu_k(u_j) = \frac{q_{jk}}{s_k}, \quad j = 1,\ 2, \cdots,\ J.$$

So Eq. 3-4 defines a fuzzy relation R_f model [47],

$$r_{jk} = \mu_k(u_j) \quad and \quad R_f = (r_{jk})_{J\times K}, \quad j = 1,\ 2, \cdots,\ J; \quad k = 1,\ 2, \cdots,\ K.$$

which changes Q into a fuzzy set and illustrates the fuzzy relationship between different dimension factors. □

3.2 Principle of Information Diffusion

Theorem 3.1 Principle of Information Diffusion [47] Let $X = \{x_i | i = 1, 2, \ldots, n\}$ be a given sample which can be used to estimate the relationship R on universe V and γ be a reasonable operator. Using it to deal with X directly, we can obtain an estimator about R, denoted as $\hat{R}(\gamma, X)$. If and only if X is incomplete, there must exist a reasonable diffusion function $\mu(x_i, u)$ and a corresponding operator γ' which can transform X into the *fuzzy sample set* $D(X)$. So it can lead to a diffusion estimator $R'(\gamma', D(x))$ such that

$$\|R - R'\| < \|R - \hat{R}\|.$$

Where $\|\cdot\|$ denotes the error between the real relationship and the estimated one.

The relationship can be shown as Fig. 3-1 and this principle holds for the following inferences.

Corollary 3.1 Normal Information Diffusion Estimator Suppose $\mu(x_i, u_j)$ is given by Eq. 3-1, let

$$q_j = \sum_{i=1}^{n}\mu(x_i, u_j) = \sum_{i=1}^{n} p_{ij} \quad and \quad Q = (q_j) \quad j = 1, 2, \ldots, J. \tag{3-4}$$

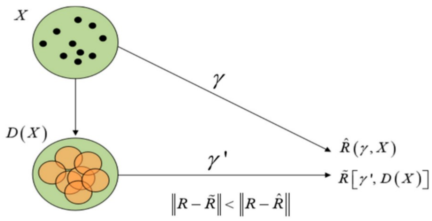

Figure 3-1 The principle of information diffusion method

where Q means the amount of information diffusion from the sample point to the monitoring point. All the diffusion amounts form a fuzzy set, that is, the sample point has been transformed into a fuzzy set Q. Define

$$H = \sum_{j=1}^{J} q_j, \tag{3-5}$$

according to Def. 4 and Thm. 3.1, the normal information diffusion estimator with respect to probability density function can be denoted by matrix P and the equation can be defined as Eq. 3-6.

$$p_j = q_j/H, j = 1, 2, \cdots, J; \quad and \quad P = (p_j) \quad j = 1, 2, \ldots, J. \tag{3-6}$$

Corollary 3.2 **Max-min inference for** R_f Suppose the input-output relationship R_f is given by Def. 5, where input fuzzy set is A and output fuzzy set is B. The fuzzy output B can be explained with membership function by using the approximate reasoning operator, i.e.,

$$\mu_B(v_k) = \max_{u_j \in U}\{\mu_A(u_j), r_{jk}\}, \quad v_k \in V. \tag{3-7}$$

Further, for two dimensional input sets A where $A_i = (u_j, v_k)$ and output sets B where $B_i = o_l$, the fuzzy membership function $\mu_B(o_l)$ can be denoted as

$$\mu_B(o_l) = \max_{\substack{u_j \in U \\ v_k \in V}}\{\min \mu_A(u_j, v_k), r_{jkl}\}, \quad o_l \in O. \tag{3-8}$$

Based on Thm. 3.1, it can be proved that the max-min fuzzy composition rule Eq. 3-8 can make more accurate inference for R_f model when the sample sets are incomplete.

Chapter 4 Dynamic Probability Risk Assessment Model

The results of risk assessment play an increasingly important role in disaster management, and can guide emergency management departments to prepare the corresponding emergency plans. There are many papers focus on risk assessment, such as considering the trigger factors and morphological parameters, vulnerability curve and exposure assessment [49]. Huang [14] put forward the concept of probabilistic risk, which can be quantified as the expected value of hazard influence to predict risk based on historical data. The randomness caused by inherent stochastic variability and incomplete sample sets in flood [38] and drought [31] risk assessment has been solved. Zhong et al. [32] proposed the combined cloud-based information diffusion method and analytic hierarchy process model to deal with comprehensive risk evaluation problems with various indexes. However, there is little research discussing the uncertainness of multiple hazards and considering the dynamic risk. In one hand, the definition of integrated probabilistic risk has been proposed by Huang [50] and the concept of dynamic risk can be estimated by conditional probability estimator [37]. On the other hand, the problem of assessing integrated probabilistic risk dynamically when data sets are incomplete remains to be solved.

This chapter aims at combining the variable fuzzy sets theory with information diffusion method (VFS-IDM) to assess integrated probability risk dynamically when the given data sets are incomplete. By converting the multiple dimension indicators of the samples into a single degree value, the fuzzy sets theory deals with uncertainties interval and provides an appropriate tool to solve integrated risk. Then, information diffusion method can be used to change each sample point into a fuzzy set for improving the accuracy of the relationship of probability distribution and vulnerability curve. Based on the proposed model, this chapter takes the time dimension into consideration to assess the multiple hazards risk dynamically. The process of building the VFS-IDM model has been given in the following content.

4.1 Improved Probabilistic Risk

By the previous study, the risk could be classified into four categories: pseudo risk, probability risk, fuzzy risk, and uncertainty risk [50]. There are many papers focusing on the above four risks, but the research on dynamic probability risk is still lacking. In the following section, the definition of probability risk and fuzzy risk will be introduced first, then the main research goal of this research will also be specified.

Definition 6 *A probability risk* is the scene associated with some specified adverse incident that we are able to statistically predict it by using probability model and historical data. Such risk relates to the events with random uncertainty and give the result of hazards occurring or not. *A fuzzy risk* contains fuzzy uncertainness related to the corresponding events having fuzzy boundaries or the information we have for prediction is incomplete. It refers the specified adverse incident that can be inferred approximately by using fuzzy logical. The above definition of risk can be quantified as the expected value of hazards influence, shown in the following equation

$$Risk = \int probabilitydistribution \cdot vulnerabilitycurve \, d(factor). \qquad \square$$

There are some limitations when confronting the multiple hazards events which are characterized by fuzzy boundaries and the information contained in data sets is limited when data sets are incomplete. Based on these two definitions, we can define the improved probabilistic risk.

This section combines the variable fuzzy set (VFS) theory with information diffusion method (IDM) to assess integrated probability risk dynamically. The *Improved probabilistic risk* is the scene in the future associated with multiple adverse incident, which is the expected value of hazards influence and can be assessed dynamically by using variable fuzzy sets theory and information diffusion method. The improved probabilistic risk can not only assess multiple hazards risk more precise but also give the result which can be shown as dynamic risk.

From the definition of improved probabilistic risk, the most important thing is to estimate the probability density and vulnerability curve when data set are incomplete. To more specifically, the probability distribution $p(x)$ of the occurrence of hazards with respect to the factor x can be estimated by some formulas of frequency or probability model, and the input-output relationship of $f(x)$ between the factor and losses can also be estimated by fuzzy model. So the probabilistic risk can be quantified as the expected value of hazards influence, just as shown in Eq. 4-1 and the relationship can be shown as Fig. 4-1.

$$Risk = \int p(x) \cdot f(x)\, dx = \sum_{j=1}^{J} p(x; u_j) \cdot f(x; u_j). \tag{4-1}$$

where the density function represents the probability of the risk happen with respect to

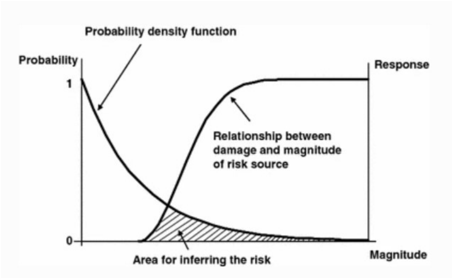

Figure 4-1 The expected value of improved probabilistic risk

magnitude and the relationships between losses and magnitude represent the vulnerability curve. Then the meaning of improved probabilistic risk can be interpreted by the expected value of hazards influence which is the same as the risk level. The following section focuses on how to calculate the expected probability risk based on historic data sets.

4.2 VFS-IEM for Comprehensive Evaluation

When we study the multiple natural hazards risk system, there are many indicators to represent the levels of integrated risk which makes the assessment process more complex. Besides, the collected data set always described as class intervals and it will make the problem more vague and uncertain in the assessment. By the definition of improved probabilistic risk, the variable fuzzy sets method can be used to improve the reliability of evaluation results. So, in this chapter, the VFS-IEM model can be used to deal with original data sets and then get more reliable result in integrated risk assessment. According to the VFS-IEM comprehensive evaluation model (2-22), here are the steps which converts the multiple dimension classes of the data sets into one dimension degree value.

- Step 1: The interval criterion matrix can be expressed as I_{ab} which is given by the classes standard of different indicator.

$$I_{ab} = ([a, b]_{rl}),$$

where $[a, b]_{rl}$ denotes the value of rth indicator for lth class.

- Step 2: Based on the interval criterion matrix denoted by I_{ab}, another interval matrix I_{cd} can be constructed as:

$$I_{cd} = ([c,d]_{rl}),$$

where $[c,d]_{rl}$ denotes the value of adjacent interval from rth indicator for lth class.

- Step 3: Find out the balance boundaries M_{rl} of fuzzy sets by Eq. 2-4, then matrix M is expressed by:

$$M = \frac{L-l}{L-1}a_{rl} + \frac{l-1}{L-1}b_{rl} = (M_{rl}).$$

- Step 4: IEM to decide the weights of indicators, the entropy coefficient of rth indicator can be evaluated by Eqs. 2-12 and 2-13:

$$\begin{cases} f_{rl} = u_{rl}/\sum_{l=1}^{L} u_{rl} \\ h_r = -1/lnn \cdot \sum_{l=1}^{L}(f_{rl} ln f_{rl}) \\ \omega_r = (1-h_r)/(R - \sum_{r=1}^{R} h_r \end{cases}.$$

- Step 5: By the calculation equations of relative membership degree Eqs. 2-9 2-10 2-11, the relative membership matrix of each sample can be denoted as $\mu_A(u)$ with degree value from rth indicator for lth class:

$$\mu_A(u) = (\mu_A(u)_{rl}).$$

- Step 6: Combine with the class weights ω_r, the comprehensive degree value of each sample denotes as Eq. 2-22 and the result is:

$$\nu_A(u)_l = \frac{-1}{1 + (\frac{\sum_{r=1}^{R}[\omega_r(1-\mu_A(u)_{rl})]^\alpha}{\sum_{r=1}^{R}[\omega_r \mu_A(u)_{rl}]^\alpha})^{\frac{\beta}{\alpha}}}.$$

- Step 7: Integrate the ranking feature value to get the degree value of multiple hazards

$$H = (1 \quad 2 \ldots L) \cdot (\nu_A^o(u)_l)^T.$$

The comprehensive evaluation model based on variable fuzzy sets theory effectively eliminates the border effect on assessment result and minimizes the estimation standard error. For integrated hazards risk analysis, this chapter applies the VFS-IEM comprehensive evaluation model to deal with the multiple indicators and then simplify the evaluation problem. By doing this process, the fuzziness in data sets has been eliminated and we have the sample sets that reflect the degree value of multiple hazards level, so that we can use the processed samples to estimate the relationships between data sets by applying information diffusion method.

4.3 Normal Information Diffusion Estimator

The recorded data sets of natural hazards are incomplete when assessing the integrated dynamic risk, so this section proposes the information diffusion method to compensate the limited information caused by incomplete sample sets. Bases on the processing of variable fuzzy set dimension reduction model and the incompleteness of time series data, in order to obtain better estimation accuracy, information diffusion method can be used to blur the data points to make up the defect of limited information. There are many types of information diffusion functions. It can be proved that the normal information diffusion (NID) function is better than anyone when the sample sets are incomplete [47]. So, based on the definitions of normal information diffusion method introduced in chapter three, this section applies the normal information diffusion (NID) estimator to get the information matrix Q and then makes the inferences for incomplete data sets, here are the results.

4.3.1 Conditional Probability Distribution

By the Inference One 3.1 in chapter three, we get the normal information diffusion estimator in discrete probability density function p_j.

$$p_j = \frac{\sum_{i=1}^{n} \mu(x_i, u_j)}{\sum_{j=1}^{J} \sum_{i=1}^{n} \mu(x_i, u_j)}, j = 1, 2, \cdots, J., \tag{4-2}$$

where p_j means that the frequency value of samples falling at u_j and is taken as the estimation value of probability distribution. Furthermore, for the 2-dimensional diffusion function of X on U and V,

$$\mu(x_i; u_j, v_k) = exp[-\frac{(x_i - u_j)^2}{2h^2} - \frac{(x_i - v_k)^2}{2h^2}], j = 1, 2, \cdots, J \quad ; k = 1, 2, \cdots, K., \tag{4-3}$$

We can do the same way to get the discrete joint probability distribution p_{jk}:

$$p_{jk} = \frac{\sum_{i=1}^{n} \mu(x_i; u_j, v_k)}{\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{i=1}^{n} \mu(x_i; u_j, v_k)}, j = 1, 2, \cdots, J \quad ; k = 1, 2, \cdots, K. \tag{4-4}$$

Then we can get the conditional probability distribution which is denoted by:

$$p(x; u_j) = p_{v|u_j}(v|u_j) = \frac{p_{jk}}{\sum_{k=1}^{K} p_{jk}}, j = 1, 2, \cdots J., \tag{4-5}$$

and Eq. 4-5 can be used to represent the conditional probability of the hazards occurrence, and describe the occurrence probability of a certain type hazards.

4.3.2 Vulnerability Curve

For a fuzzy input A with membership function $\mu(x_i; u_j, v_k)$ defined by Def. 2 and fuzzy relation R_f model defined by Def. 5, the Inference Two 3.2 has proved that the fuzzy output B with membership function $\mu_B(o_l)$:

$$\mu_B(o_l) = \max_{\substack{u_j \in U \\ v_k \in V}} \{\min \mu_A(u_j), r_{jkl} \quad \min \mu_A(v_k), r_{jkl}\}, \quad l = 1, 2, \cdots, L., \tag{4-6}$$

can make more accurate inference for R_f model when the sample sets are incomplete. Then the weighted value $f(x; u_j, v_k)$ defined by the center-of-gravity method [37] can estimate vulnerability curve more precise and the result of Eq. 4-7

$$f(x; u_j, v_k) = \frac{\sum_{l=1}^{L} \mu_B(o_l) \cdot o_l}{\sum_{l=1}^{L} \mu_B(o_l)} \quad j = 1, 2, \cdots, J \quad ; k = 1, 2, \cdots, K., \tag{4-7}$$

is the discrete vulnerability curve constructed by 3-dimensional diffusion function.

4.4 VFS-IDM Dynamic integrated Probability Risk Model

So far, the corresponding calculation formulas and derivation process of the VFS-IDM model have been given. From the above equations, we have the following steps to calculate the conditional probability distribution and vulnerability curve and the expected value of dynamic multiple hazards risk can be given.

- Step 1: Eliminate the fuzziness of multiple hazards data sets by using VFS-IEM model 2-7.
- Step 2: Construct the information matrix with each samples by using normal information diffusion function.
- Step 3: Change the information matrix into probability matrix or fuzzy relationship matrix based on the characteristic of information matrix.
- Step 4: Get the result of conditional probability distribution and vulnerability curve based on Eqs. 4-5, 4-7.
- Step 5: Calculate the expected value of integrated probability risk by Eq. 4-1.

This chapter combines the variable fuzzy set with information diffusion method (VFS-IDM) to assess integrated probability risk dynamically when the given data sets are multiple index and incomplete. The VFS-IDM model can be concluded in the following Fig. 4-2. In the next chapter, the case study of rainstorm and typhoon dynamic risk evaluation will be given to illustrate the model work.

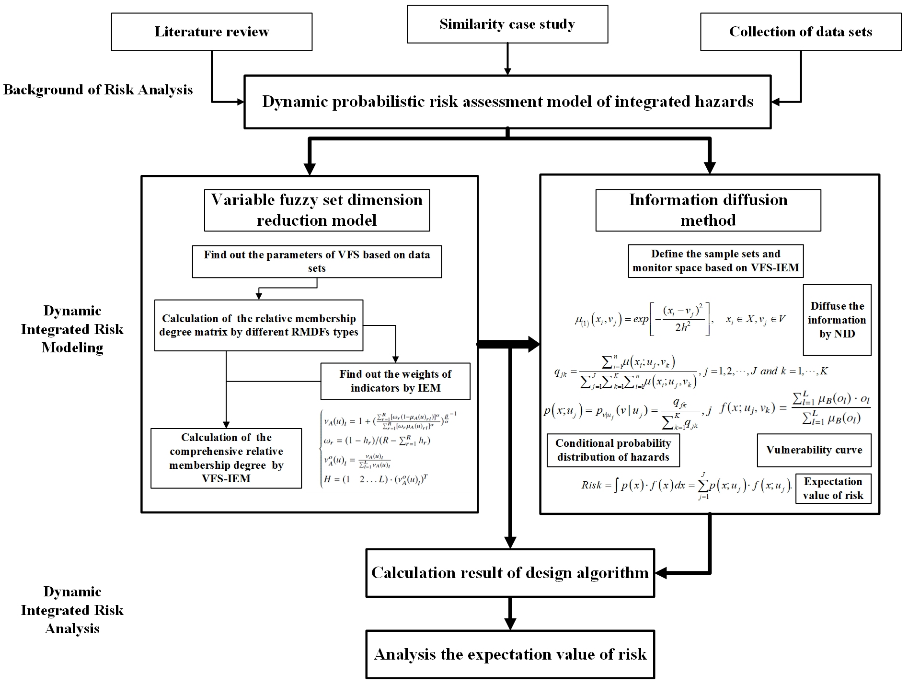

Figure 4-2 Flow chart of the VFS-IDM dynamic integrated probability risk assessment model

4.5 Brief Summary

In this chapter, we propose a new model to evaluate multiple hazards dynamic risk. The model can effectively convert the multiple dimension indicator of samples into a single degree value and then improve the accuracy of relative membership degree calculation for assessing multiple hazards risk. The proposed model changes the sample point into a fuzzy set and improves the accuracy of conditional probability distribution and vulnerability curve estimation. To improve the accuracy of risk evaluation results, the expected value of multiple hazards dynamic risk can be calculated by using the normal information diffusion estimator. Fig. 4-2 has shown the modeling procedure of VFS-IDM.

Chapter 5 Case Study

Shenzhen is located in the southern part of Guangdong province, as China's first special economic zone, it covers an area of $1996.85km^2$ and contains 10 districts. Shenzhen lies on the east bank of the Zhujiang River and is surrounded by Daya Bay and Dapeng Bay (shown as Fig. 5-1), where the climate is a subtropical maritime with the annual precipitation of $1933.3mm$ [51]. The coastal city is particularly vulnerable to the meteorological phenomenon, so the typhoon and rainstorm are undoubtedly the most frequency occurrence hazards in Shenzhen. According to the collected data, from 1980 to 2016, on average, the directed economic damage of the typhoon and rainstorm hazards to the Shenzhen area exceeds 360 million RMB per year, causes about 3.4 deaths annually and affects $149,000$ people [4]. The assessment results of rainstorm and typhoon risk are the basis on whether or not the early warning systems could respond and reasonably be implemented. So it is meaningful to propose a useful model to assess rainstorm induced hazards dynamic risk in Shenzhen.

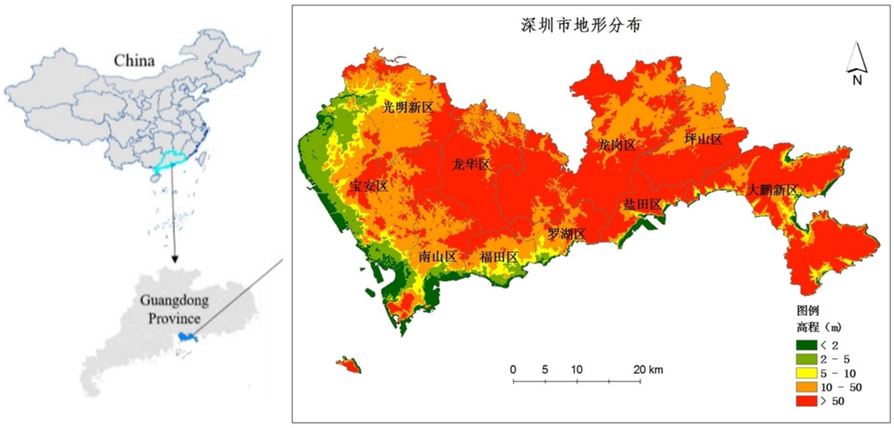

Figure 5-1 Location of ShenZhen city, Guangdong province, China

However, the historical data sets are limited and the rainstorm induced hazards have many indicators to evaluate the hazards degree level. So, in this chapter, the case study of dynamic risk evaluation caused by rainstorm and typhoon is given so as to assess the risk of direct economic loss by using the VFS-IDM model (4.4). Furthermore, the corresponding theoretical guidance for emergence management in Shenzhen has been concluded. The evaluation of rainstorm and typhoon dynamic risk based on VFS-IDM model comprises of the following steps:

- Step 1. Analysis the sample sets and select the indicators for evaluation of rainstorm and typhoon hazards level.
- Step 2. Convert the multiple dimension indicator of data sets into a single value based on variable fuzzy set dimension reduction model.
- Step 3. Turn the comprehensive level degree into a fuzzy set and then get the conditional probability density and vulnerability surface estimator based on information diffusion method.
- Step 4. Calculate the expected value of rainstorm and typhoon dynamic risk.

5.1 Data Description

The sample sets are the foundation of risk modeling, so the historical data sets should be collected in a reasonable way, especially for the multiple hazards risk assessment. Since most hazards assessment systems are constantly changing, this randomness naturally cannot ensure the reliability of risk assessment results. In probability theory, the Markov property of time series indicates that the data sets have an inherent pattern so that it can ensure the changes of future system are the same as the past random change patterns. So the data sets need to be verified and the Stationary Markov Process can ensure the reliability of the assessment model. Honestly, the incomplete data sets which are collected by short time serial historical data satisfy the Stationary Markov Process. So for the typhoon and rainstorm hazards risk assessment, the useful data sets, collected from Meteorological Bureau of ShenZhen Municipality (http://weather.sz.gov.cn/qixiangfuwu/qihoufuwu/qihouguanceyupinggu/nianduqihougongbao/) and TYPHOON ONLINE (http://typhoon.nmc.cn/web.html), have been sorted out in Tab. 5-1. In the table, MP denotes as Maximum Precipitation, SWI denotes as Strong Wind Intensity, DEL denotes as Direct Economic. And we denote the Transformed Location Number as the landing location by using expertise knowledge.

Table 5-1 Data sets of typhoons and rainstorms hazards in Shenzhen

Time	MP (mm)	SWI (m/s)	Landing Location	Transformed Location	DEL (Billion)
20090627	67.3	16.8	惠州	8.5	0.3819
0719	80	27.3	深圳	10	1.152
0915	127.9	28	台北	6	1.075
20100724	54.3	16.2	湛江	6.5	0.2571

Time	MP (mm)	SWI (m/s)	Landing Location	Transformed Location	DEL (Billion)
0912	62.4	13.7	泉州	3	0.345
0922	51.9	15.8	河源	7	0.2983
20110624	41.7	14	阳江	4.5	0.0765
0930	117.3	15.2	文昌	2.5	0.8243
20120630	33.6	16.8	珠海	6.5	0.6873
0724	152.3	24.9	台山	7	2.241
0817	66.1	13.5	湛江	3	0.9153
20130615	36.5	12.4	文昌	4	0.3621
0702	38.6	13.9	湛江	3	0.2561
0802	40.7	14.7	文昌	3	0.0851
0814	47.8	14.2	阳西	3	0.6413
0922	72.4	21.6	汕尾	8.5	1.152
20140718	34.6	14.7	文昌	2.5	0.0841
0916	73.5	18.9	徐闻	2.5	0.9641
0823	69.4	13.6	汕尾	10	1.041
1004	108.5	13.5	湛江	5.5	0.9631
20160802	166	19.2	深圳	10	2.31
0818	45.5	11.1	湛江	5.5	0.0314
1018	117.6	12.3	万宁	1.5	0.421
1021	83.7	18.8	汕尾	7.5	0.8721
20170612	161.8	23	深圳	10	2.109
0723	33.4	18	香港	9	0.5315
0823	56.3	23.9	珠海	8.5	1.328
0827	114.5	17.5	江门	8.5	1.741
0903	82.4	14.4	汕尾	7.5	0.9631
1016	40	20.3	湛江	7.5	0.7341
20180606	97.2	10.8	徐闻	8.5	0.9267
0718	50.7	11.1	万宁	1.5	0.0267
0811	45.3	10.8	阳江	7	0.5241
0916	173.5	30	台山	7.5	2.361
20190703	48.8	11	万宁	1.5	0.0672
0811	178.5	14.1	文昌	5.5	0.9561
0824	97.6	12.7	漳州	6	0.5931
0902	86.9	11.3	万宁	1	0.0751

The above data sets have been verified that satisfying the stationary Markov process and can be used to evaluate typhoon-rainstorm hazards risk. On the other hands, the multiple hazards are depicted by three indicators, so the variable fuzzy set dimension reduction model can be used to get more precise hazards level. According to the Classification Standards of Rainstorm and Typhoon, four hazard levels are developed and the index classification criteria are listed in the following table.

Table 5-2 Classification standards of rainfall and typhoon hazards

Indicators	Multiple Hazards Level			
	I	II	III	IV
Maximum Precipitation	(0,50)	(50,100)	(100,150)	(150,250)
Strong Wind Intensity	(8,10.8)	(10.8,17.2)	(17.2,23.6)	(23.6,30)
Transformed Location Number	(0,2)	(2,5)	(5,8)	(8,10)

The four classes of rainstorm and typhoon hazards level (D) in the ShenZhen area include type I expressed as $D \in [1.5, 2)$, type II expressed as $D \in [2, 2.7)$, type III expressed as $D \in [2.7, 3.5)$, and type IV expressed as $D \in [3.5, 4]$. To be honest, the category results are based on expert experience and relevant government documents.

5.2 Transfer the Observations into One Dimension Degree Value

We use the variable fuzzy set dimension reduction model introduced in chapter Two to get the comprehensive hazards level value D. Tab. 5-1 gives 38 sample points, each point can be converted into comprehensive hazards degree level by VFS-IEM model 4.2. Here are the results:

On the classes standard of different indicator, shown in Tab. 5-2, the interval criterion matrix can be expressed as Eqs. 5-1 and 5-2

$$I_{ab} = \begin{bmatrix} (0,50) & (50,100) & (100,150) & (150,250) \\ (8,10.8) & (10.8,17.2) & (17.2,23.6) & (23.6,30) \\ (0,2) & (2,5) & (5,8) & (8,10) \end{bmatrix} = ((a,b)_{rl}), \tag{5-1}$$

$$I_{cd} = \begin{bmatrix} (0,100) & (0,150) & (50,250) & (100,250) \\ (8,17.2) & (8,23.6) & (10.8,30) & (17.2,30) \\ (0,5) & (0,8) & (2,10) & (5,10) \end{bmatrix} = ((c,d)_{rl}), \tag{5-2}$$

the balance boundaries matrix M_{rl} defines as Eq. 5-3

$$M = \begin{bmatrix} 0 & 66.7 & 133.3 & 250 \\ 8 & 12.9 & 21.5 & 30 \\ 0 & 3 & 7 & 10 \end{bmatrix} = (M_{rl}). \tag{5-3}$$

Then the relative membership degree matrix can be calculated by Eqs. 2-9,2-11 and 2-10 respectively. Taking sample point $(MP = 33.4, SWI = 18, TL = 9)$ for example, the relative membership degree matrix is expressed by Eq. 5-4 where the value represents the probability of each indicator belong to hazards degree level.

$$\mu_A(u) = \begin{bmatrix} 0.666 & 0.334 & 0.000 & 0.000 \\ 0.000 & 0.438 & 0.593 & 0.063 \\ 0.000 & 0.000 & 0.333 & 0.667 \end{bmatrix}. \tag{5-4}$$

The result shows that the calculation process of RMD is worked and here are other relative membership degree matrix result which can be verified by RMDFs.

$$\mu_A(MP = 73.5, SWI = 18.9, TL = 2.5) = \begin{bmatrix} 0.265 & 0.898 & 0.235 & 0.000 \\ 0.000 & 0.367 & 0.689 & 0.133 \\ 0.417 & 0.750 & 0.083 & 0.000 \end{bmatrix}$$

$$\mu_A(MP = 97.2, SWI = 10.8, TL = 8.5) = \begin{bmatrix} 0.028 & 0.542 & 0.472 & 0.000 \\ 0.500 & 0.500 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.417 & 0.583 \end{bmatrix}.$$

To get the comprehensive hazards degree level, the information entropy method can be used to get the weight of each indicator and the result is ω, which implies that the Maximum Precipitation and Location play main role in determining the rainstorm and typhoon hazard level.

$$\omega = \begin{pmatrix} 0.43 & 0.19 & 0.39 \end{pmatrix}. \tag{5-5}$$

The result is determined by object matrix O_M Eq. 5-6 and O_M is constructed by hazards degree classification criteria.

$$O_M = \begin{bmatrix} 50 & 100 & 150 & 250 \\ 10.8 & 17.2 & 23.6 & 30 \\ 2 & 5 & 8 & 10 \end{bmatrix}. \tag{5-6}$$

Based on the VFS-IEM comprehensive evaluation model (2-22), the rainstorms and typhoons hazards level of sample point $(MP = 33.4, SWI = 18, TL = 9)$ $D = 2.75$ when hyper-parameter $\alpha = \beta = 1$, and $D = 2.18$ when hyper-parameter $\alpha = \beta =$

2. To be more general, this section takes the average of $D = 2.75$ and $D = 2.18$ to denote the rainstorms and typhoons hazards final degree level, that is $D = 2.47$. For all sample points, the following Tab. 5-3 has shown that the rainstorms and typhoons hazards comprehensive degree level.

Table 5-3 Comprehensive hazards degree level in ShenZhen

Time	$\alpha = \beta = 1$	$\alpha = \beta = 2$	Average Level (D)	Comprehensive Degree Level
20090627	3.07	2.36	2.72	III
0719	3.34	2.65	3.00	III
0915	3.93	3.55	3.74	IV
20100724	2.67	1.96	2.32	II
0912	2.68	2.29	2.49	III
0922	3.02	2.45	2.74	III
20110624	2.12	1.73	1.93	I
0930	2.87	2.57	2.72	III
20120630	2.66	1.95	2.31	II
0724	3.97	3.93	3.95	IV
0817	2.8	2.32	2.56	II
20130615	2.08	1.79	1.94	I
0702	2.28	1.7	1.99	I
0802	1.65	1.4	1.53	I
0814	2.22	2.03	2.13	II
0922	3.44	2.67	3.06	III
20140718	1.93	1.73	1.83	I
0916	2.65	2.3	2.48	II
0823	3.19	2.64	2.92	III
1004	3	2.91	2.96	III
20160802	3.66	3.69	3.68	IV
0818	1.96	1.8	1.88	I
1018	2.52	2.03	2.28	II
1021	33.1	2.91	3.11	III
20170612	3.69	3.83	3.76	IV
0723	2.52	1.7	2.11	II
0823	2.89	2.03	2.46	II
0827	3.35	3.04	3.2	III
0903	3.22	2.83	3.03	III
1016	2.95	2	2.48	II

Time	$\alpha=\beta=1$	$\alpha=\beta=2$	Average Result	Comprehensive Degree Level
20180606	2.75	2.18	2.17	II
0718	1.57	1.45	1.51	I
0811	2.72	2.17	2.45	II
0916	3.87	3.98	3.93	IV
20190703	1.52	1.48	1.5	I
0811	3.25	2.79	3.02	III
0824	2.96	2.83	2.9	III
0902	1.93	1.67	1.8	I

From the results, this section has proved that the multiple hazards level has been reasonably evaluated by comprehensive degree level which shows that the most frequent occurrence of hazards level is type III.

5.3 Dynamic Probabilistic Risk of Rainstorm and Typhoon

For now, the data sets of rainstorms and typhoons risk assessment have been processed (Tab. 5-4), but the data sets are incomplete when assessing the dynamic risk, so this section applies the information diffusion method to compensate the limited information caused by incomplete sample sets.

Table 5-4 Transformed data sets in ShenZhen

Time	Transformed Time (T)	Comprehensive Hazard Level (D)	Direct Economic Loss (L,Billion)
20090627	176	2.72	0.3819
0719	198	3	1.352
0915	254	3.74	1.3750
20100724	203	2.32	0.2571
0912	251	2.49	0.4450
0922	261	2.74	0.9831
20110624	173	1.93	0.0765
0930	269	2.72	0.4013
20120630	179	2.31	0.2895
0724	203	3.95	2.48
0817	226	2.56	0.7648
20130615	164	1.94	0.1527
0702	181	1.99	0.1894
0802	211	1.53	0.0452

Time	Transformed Time (T)	Comprehensive Hazard Level (D)	Direct Economic Level (L)
0814	223	2.13	0.1423
0922	261	3.06	1.2351
20140718	197	1.83	0.0841
0916	255	2.48	0.7682
0823	232	2.92	0.7410
1004	273	2.96	0.8352
20160802	211	3.68	2.1521
0818	227	1.88	0.0251
1018	287	2.28	0.2362
1021	290	3.11	0.9341
20170612	161	3.67	2.058
0723	202	2.11	0.2461
0823	232	2.46	1.31
0827	236	3.2	1.613
0903	242	3.03	1.8872
1016	285	2.48	0.5902
20180606	155	2.47	0.6952
0718	197	1.58	0.0267
0811	220	2.45	0.5241
0916	255	3.93	2.226
20190703	182	1.49	0.0528
0811	210	3.02	0.8182
0824	233	2.9	0.8391
0902	241	1.8	0.0725

From Tab. 5-4, considering the time dimension T, we obtain the sample observations on direct economic loss L over each multiple hazards comprehensive degree level D, written as

$$\begin{aligned} Sample &= \{(t_1, d_1, l_1), \ldots, (t_i, d_i, l_i), \ldots, (t_{38}, d_{38}, l_{38})\} \\ &= \{(172, 2.72, 0.3819), \ldots, (241, 1.8, 0.0725)\} \end{aligned}. \tag{5-7}$$

where t_i, d_i represents the time dimension of hazards occurrence and the comprehensive degree level respectively, and l_i is the directed economic loss caused by maximum precipitation and strong wind intensity.

The most important part of improved probability risk is how to estimate the probability density and vulnerability curve when data sets are incomplete. In the following contents, the probability distribution $p(x)$ of the occurrence of hazards can be estimated by the probability model, and the input-output relationship of hazards degree level and direct economic losses can be estimated by a fuzzy model. Then the dynamic probability risk can be quantified as the expected value of hazards influence, just as shown in Eq. 4-1.

5.3.1 Conditional Probability Function

To estimate the conditional probability distribution $p(x)$ of the occurrence of hazards degree level D over the time dimension T, we have sample points (t_i, d_i), just shown as Tab. 5-4 and Eq. 5-7. Then the diffusion coefficients can be calculated by using Eq. 3-2, written as

$$\begin{cases} h_t = 2.6581 \cdot (290 - 155)/(38 - 1) = 10 \\ h_d = 2.6581 \cdot (3.95 - 1.37)/(38 - 1) = 0.19 \end{cases} . \tag{5-8}$$

Then by the 2-dimensional normal diffusion formula in Eq. 4-3, the information matrix can be obtained by

$$Q2 = \begin{array}{c} \\ t = 164 \\ t = 194 \\ t = 224 \\ t = 254 \\ t = 284 \end{array} \begin{array}{c} d = 1.8 \; d = 2.4 \; d = 3.0 \; d = 3.6 \\ \begin{bmatrix} 1.46 & 1.14 & 0.18 & 0.89 \\ 1.88 & 1.28 & 1.27 & 0.35 \\ 1.55 & 2.86 & 2.22 & 0.48 \\ 0.46 & 2.13 & 2.15 & 1.02 \\ 0.04 & 1.81 & 1.47 & 0.04 \end{bmatrix} \end{array} . \tag{5-9}$$

Further, employing the discrete probability density function in Eqs. 4-4 and 4-5, we have joint probability density function P (Eq. 5-10) and conditional probability function P_{con} (Eq. 5-11). By the assumption, we mean the monitor space $T = (t = 164, t = 194, t = 224, t = 254, t = 284)$ equals to month $(June, July, August, September, October)$ and $D = (d = 1.8, d = 2.4, d = 3.0, d = 3.6)$ equals to hazard level (I, II, III, IV).

$$P = \begin{array}{c c} & \begin{array}{cccc} I & II & III & IV \end{array} \\ \begin{array}{c} June \\ July \\ August \\ September \\ October \end{array} & \begin{bmatrix} 0.059 & 0.046 & 0.007 & 0.036 \\ 0.076 & 0.052 & 0.051 & 0.014 \\ 0.063 & 0.116 & 0.090 & 0.019 \\ 0.019 & 0.086 & 0.087 & 0.041 \\ 0.002 & 0.073 & 0.060 & 0.002 \end{bmatrix} \end{array}, \quad (5\text{-}10)$$

$$P_{con} = \begin{array}{c c} & \begin{array}{cccc} I & II & III & IV \end{array} \\ \begin{array}{c} June \\ July \\ August \\ September \\ October \end{array} & \begin{bmatrix} 0.398 & 0.311 & 0.049 & 0.243 \\ 0.393 & 0.268 & 0.266 & 0.073 \\ 0.218 & 0.402 & 0.312 & 0.068 \\ 0.080 & 0.370 & 0.373 & 0.177 \\ 0.012 & 0.539 & 0.437 & 0.012 \end{bmatrix} \end{array}. \quad (5\text{-}11)$$

From the above results, it can be seen that on the one hand, the hazards occurrence possibility of various types hazards will be the highest in August and the type II and III hazards level is most likely to occur in August and September. On the other hand, the probability of type I hazards level occurring in June and July is the highest, the probability of hazard level II occurring in August and October is the highest, and the highest probability of type III hazard level occurs in September.

5.3.2 Vulnerability Surface

The definition of improved probabilistic risk asks for estimating the input-output relationship between the factor and losses. We need to estimate the vulnerability surface $f(x)$ between the hazards degree level D and direct economic losses L over time dimension T. Based on the sample points (t_i, d_i, l_i), just shown as Tab. 5-4 and Eq. 5-7, the *$n-$ dimension diffusion fuction* give the formula of three dimension diffusion estimator (Eq. 5-12) and the diffusion coefficients can be written as Eq. 5-13.

$$\mu(x_i; u_j, v_k, o_l) = exp[-\frac{(x_i - u_j)^2}{2{h_t}^2} - \frac{(x_i - v_k)^2}{2{h_d}^2} - \frac{(x_i - o_l)^2}{2{h_l}^2}],$$
$$where \quad x_i \in X, j = 1, 2, \cdots, J \quad, k = 1, 2, \cdots, K \quad, l = 1, 2, \cdots, L. \quad (5\text{-}12)$$

$$\begin{cases} h_t = 2.6581 \cdot (290 - 155)/(38 - 1) = 10 \\ h_d = 2.6581 \cdot (3.95 - 1.37)/(38 - 1) = 0.19 \\ h_l = 2.6581 \cdot (2.48 - 0.0251)/(38 - 1) = 0.1764 \end{cases} . \tag{5-13}$$

Then by the definition of primary information matrix, the 3-dimension information matrix result can be obtained by $Q3$.

$$Q3 = \left(\begin{array}{cc} & l=0.1\ l=0.4\ l=0.7\ l=1.0\ l=1.3\ l=1.6\ l=1.9\ l=2.2 \\ t=164 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 1.40 & 0.47 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.27 & 0.46 & 0.76 & 0.16 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.05 & 0.18 & 0.04 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.36 & 0.60 & 0.65 \end{bmatrix} \\ t=194 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 1.75 & 0.54 & 0.02 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.79 & 0.90 & 0.13 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.04 & 0.29 & 0.30 & 0.89 & 0.34 & 0.01 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.01 & 0.00 & 0.08 & 0.28 \end{bmatrix} \\ & \vdots \\ t=284 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 0.03 & 0.03 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.62 & 1.10 & 0.82 & 0.09 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.03 & 0.16 & 0.40 & 0.84 & 0.80 & 0.33 & 0.51 & 0.10 \\ 0.00 & 0.00 & 0.01 & 0.03 & 0.01 & 0.00 & 0.00 & 0.00 \end{bmatrix} \end{array} \right) . \tag{5-14}$$

According to the formula in Eq. 4-6, we obtain a fuzzy relationship which takes time dimension T, hazards level D as input and the loss O as output. The result can be denoted as R.

$$R = \left(\begin{array}{cc} & l=0.1\ l=0.4\ l=0.7\ l=1.0\ l=1.3\ l=1.6\ l=1.9\ l=2.2 \\ t=164 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 0.80 & 0.43 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.15 & 0.42 & 0.57 & 0.15 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.05 & 0.13 & 0.04 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.08 & 1.00 & 1.00 \end{bmatrix} \\ t=194 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 1.00 & 0.49 & 0.01 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.45 & 0.82 & 0.10 & 0.01 & 0.01 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.04 & 0.22 & 0.28 & 1.00 & 0.94 & 0.02 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.01 & 0.00 & 0.13 & 0.43 \end{bmatrix} \\ & \vdots \\ t=284 \begin{array}{c} d=1.8 \\ d=2.4 \\ d=3.0 \\ d=3.6 \end{array} & \begin{bmatrix} 0.02 & 0.03 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.35 & 1.00 & 0.61 & 0.08 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.02 & 0.15 & 0.56 & 1.00 & 0.19 & 0.03 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.01 & 0.03 & 0.01 & 0.00 & 0.00 & 0.00 \end{bmatrix} \end{array} \right). \tag{5-15}$$

Employing the Eq. 4-7, we obtain a discrete vulnerability surface in terms of direct economic loss, just shown in Eq. 5-16.

$$f(x;t,d) = \begin{array}{cc} & I\ II\ III\ IV \\ \begin{array}{c} June \\ July \\ August \\ September \\ October \end{array} & \begin{bmatrix} 0.20 & 0.02 & 0.00 & 0.00 \\ 0.24 & 0.04 & 0.00 & 0.00 \\ 0.15 & 1.13 & 1.67 & 1.90 \\ 0.05 & 0.55 & 2.67 & 2.62 \\ 0.01 & 0.02 & 0.00 & 0.00 \end{bmatrix} \end{array}. \tag{5-16}$$

The result shows that, for the Shenzhen region, most of the economic losses are concentrated in August and September. For example, $f(x;t = September, d = III) = 2.67$ means that, in the Shenzhen area, if the multiple comprehensive hazards level III occurs in September, then this type hazard level will bring 2.67 billion RMB direct economic losses. The hazards happening in these two months have caused the serious economic losses, so that the government should focus on preventing the hazards influence in these two months.

5.3.3 Dynamic Probabilistic Risk

In this research, there are incomplete sample sets (see Tab. 2-1), so it is reasonably to combine the discrete conditional probability distribution (Eq. 5-11) with vulnerability surface (Eq. 5-16) to calculate the multiple dynamic risk of typhoons and rainstorms hazards. The dynamic probabilistic risk can be quantified as the expected value of hazards influence, shown as in Eq. 4-1 and the result can be shown as Eq. 5-17.

$$Risk = \begin{pmatrix} 0.08582 & 0.10504 & 1.1372 & 1.66715 & 0.0109 \end{pmatrix}. \tag{5-17}$$

The result shows that the risk value of typhoons and rainstorms hazards in each month is different and the highest hazard risk value happens in August and September which have caused the greatest economic losses in the Shenzhen region. It can be seen from the conditional probability function that the risk value is more consistent with the distribution of hazards level in Shenzhen, so that the result can give some guidances on disaster emergency management.

5.4 Results and Discussions

Risk assessment is a very important issue in emergency management, but there is little work focusing on building mathematic model to predict integrated probability risk dynamically when the data sets are incomplete. This chapter applies the VFS-IDM model to assess the dynamic probabilistic risk caused by typhoons and rainstorms. The proposed model does not need to make too many assumptions except the historical data should satisfy Markov Process, and not only provides an appropriate tool for dealing with multiple hazards risk but also makes the results of dynamic risk more reliable. To prove that, in this chapter, we show the Shenzhen case study to assess the dynamic probabilistic risk caused by typhoons and rainstorms hazards. The results show: (i) The hazard occurrence possibility is the highest in August and the type II and III hazard level are the most likely to occur in August and September. (ii) The hazard of various levels that occur in August and September which will cause the serious economic losses. (iii) The risk value of typhoons and rainstorms hazards in each month is different and the highest hazard risk value occurs in August and September where result in the greatest economic losses for Shenzhen region.

结论及展望

1. **模型构造方法**

沿海城市深圳属于亚热带海洋季风气候，暴雨台风灾害严重制约了当地经济和社会的可持续发展。对于深圳地区的台风暴雨动态风险评估，本研究通过阅读气象年报和查阅台风网的相关信息，收集到台风暴雨灾害发生时对应的最值降水，强风强度、台风登陆点以及直接经济损失数据，提出了可变模糊集信息扩散动态风险评估模型。其中可变模糊集理论主要是消除评估标准当中的不确定性, 得到多灾种等级的综合评估结果。信息扩散理论主要针对小样本数据集中包含的不完备信息，解决小样本数据下估计结果精度不高这一问题。文中所构建的模型首先使用可变模糊集和信息熵理论来综合刻画灾害的等级，其次将得到的灾害等级数据和直接经济损失在时间变量下使用信息扩散方法计算对应灾害等级发生的条件概率密度和脆弱性曲线，最后根据期望风险的定义计算台风暴雨灾害发生的动态风险大小，以此来指导该地区的应急管理。本研究的创新点在于：(i) 根据动态风险评估这一研究对象，考虑时间因素引入动态概率风险定义。(ii) 针对多灾种评估中不同灾种的评估具有不一样的衡量指标这一问题，文中结合可变模糊集和信息熵方法，提出将多灾种的衡量指标转换为单一数值来表示多灾种灾害等级，从而提高了多灾种风险评估中灾害等级计算的准确性[36]。(iii) 基于动态概率风险的定义，文中将得到的灾害等级和灾害损失数据使用信息扩散方法求解各类灾害等级对应的条件概率分布与脆弱性曲线，通过将样本点转化为模糊集来提高条件概率分布与脆弱性曲线估计的准确性[48]。(iv) 最终根据期望概率公式计算风险，结合正态扩散所得到的灾害等级概率分布和承灾体脆弱性曲线给出多灾种的动态概率风险。

2. **主要结果**

根据深圳气象局和国家台风网的数据，本研究按照已有的灾害分类标准将台风暴雨灾害分为四个灾害等级 (见表 5-2)，并按照专家经验将时间数据和台风登陆点数据转化为能够量化的数值 (见表5-1和表5-4)，这样的处理能够更好地对灾害等级进行刻画。

通过可变模糊集和信息熵理论的运用，本研究建立了一个多指标降维模型，该模型能够处理台风暴雨灾害衡量指标的区间不确定性。文中给出计算隶属度函数的方法 (见公式2-9、公式2-10和公式2-11)，并将多灾种的等级衡量区间转化为单一的综合评估值，结果如表5-3所示。通过相互比较所得结果可知，模型给出的最终效果比较好，较为全面地描绘了深圳地区灾害等级的分布情况。台风暴雨灾害集

中发生于八、九月份，且 II、III 类灾害在过去 8 年中发生的概率最高。应急管理部门应该警惕该类台风暴雨灾害的发生，提前准备相应的应急预案，减少次生灾害的发生。

对于得到的台风暴雨等级数据，模型利用信息扩散的方法来估计各类等级灾害发生的联合概率密度、条件概率密度以及深圳地区的脆弱性曲线 (结果见公式5-10, 公式5-11 和公式5-16)。结果显示：(i) 各类等级灾害集中发生于八、九月份，且 II、III 类灾害发生的概率最高，将近每 8 年会发生一次。(ii) 从同一月份考虑不同等级灾害的发生，六、七月份发生 I 类灾害的概率最大，八、十月份发生 II 类灾害可能性最大，九月份发生 III 类灾害可能性最大，这些结论可以指导应急管理部门提前准备相应的预案，减少不必要资源的消耗。(iii) 从灾损角度来看，经济损失也集中于八、九月份，这两个月发生的各种等级灾害对经济造成的损失最大。不同月份下同一等级灾害造成的直接经济损失不相同，这说明台风和暴雨对经济的影响不完全相同；同一月份下，随着灾害等级不断升高，对深圳地区造成的经济损失程度在逐渐减弱，这说明深圳地区承灾能力阈值比较大，在现有体系下应对突发性灾害的能力比较强。

最终根据期望概率公式计算风险 (公式 5-17)，结合正态扩散所得到的灾害等级概率分布和承灾体脆弱性曲线给出多灾种的动态概率风险。得出深圳地区受到台风暴雨灾害的风险在八、九月份达到最大，平均来说分别给深圳经济带来 1.14 亿元和 1.67 亿元的损失，这一结果与灾害发生最频繁的月份相吻合，从另外一个角度也说明了文中所构建模型的正确性。

3. 今后工作及展望

文中所得到的结果虽然比较符合实际情况，但从模型构建的过程中也能找到模型可以改进的地方，比如对于不同灾害种类衡量指标的权重计算带有一定的主观性，以及承灾体脆弱性曲线的结果没有考虑到承灾体内在属性的变化，这些都是可以在模型构建方面进行优化的地方。另一方面，关于案例数据的处理方面也存在一些主观性的问题，可以考虑采取更加科学的方法处理原数据，以得到更加科学的结论。动态风险的研究是一个比较新颖的课题，本文只是从一个微小的方面进行了探讨，期望今后能够在这一方面做出一些贡献，在今后的学习中也会侧重这一方面的知识积累，以作出更有价值的研究结果。

Conclusion and Future Work

1. The Proposed Model

Shenzhen is located in the southern China, a coastal city with a lower latitude, where the rainstorm and typhoon hazards have severely restricted the sustainable development of local economy and society. To assess the dynamic risk, this research takes time dimension into consideration to introduce the concept of dynamic probabilistic risk and proposes the variable fuzzy set and information diffusion method (VFS-IDM) model. The variable fuzzy set theory is introduced to eliminate the randomness of evaluation criteria and obtaining the comprehensive evaluation results of multiple hazards level degree. The information diffusion method aims at solving the problem of limited information in dynamic risk and improving the accuracy of sample data estimation. To illustrate the proposed model, this research applies the historical data based on the maximum precipitation, strong wind intensity, landing location and direct economic losses caused by typhoons and rainstorms hazards to evaluate the dynamic risk of Shenzhen area.

There are two parts needing to illustrate in the proposed model. Since the level of multiple hazards is affected by multiple indicators, the hazard level results are often uncertain. The proposed model uses fuzzy set theory (VFS) to calculate the relative membership degree and applies information entropy method (IEM) to obtain the weights of criteria indicators for multiple hazards evaluation. Then the multiple indicators reduction model is introduced and can be used to get the comprehensive results of multiple hazards level degree. According to the concept of dynamic probabilistic risk which is charactered by insufficient data dimensions, the proposed model uses information diffusion method (IDM) to solve the problem of limited information in dynamic risk and estimate conditional probability distribution and vulnerability curve. Ultimately, based on the definition of expected risk, the proposed model calculates the rainstorm and typhoon hazards dynamic probabilistic risk to guide the emergency management in Shenzhen area. The specific innovations made by this research are: (i) Based on the definition of probabilistic risk, this research takes time dimension into consideration to introduce the concept of dynamic probabilistic risk. (ii) Considering that different kinds of hazards have different measurement indicators for the multiple hazards evaluation, a combination model of variable fuzzy sets and the information entropy method has been proposed. This model converts the multiple dimension indicators of different hazard into a single degree value so as to improve the accuracy of hazard level degree [36]. (iii) According to the concept of dynamic probabilistic risk which is charactered by insufficient data dimensions, this research applies information diffusion method to estimate conditional probability distribution and vulnerability curve by using the obtained multiple hazards degree value, time data and hazard losses. This method can solve the problem of limited information in dynamic risk and improve the accuracy of normal diffusion estimator [48]. (iv) Finally, this research calculates the expected value of conditional probability distribution and vulnerability curve to quantify multiple hazards dynamic probabilistic risk.

2. Main Results

According to the notations of Shenzhen Meteorological Bureau and the National Typhoon Online, this research divides typhoons and rainstorms hazards degree into four levels (shown as in Tab. 5-2) which is the same with the Classification Standards of Rainstorm and Typhoon Hazards. Also, this research converts time sequences and typhoons landing location data sets into quantifiable value and the results can be seen in Tab. 5-1 and Tab. 5-4.

By using variable fuzzy sets and information entropy theory, the multiple indicators reduction model has been proposed in this research. The model can deal with the fuzziness of typhoon and rainstorm hazards measurement indicators. This research presents the relative membership degree function (shown as Eq.2-9, Eq.2-10 and Eq. 2-11) and converts the multiple dimension indicators of different hazard into a single degree value. The comprehensive multiple hazards level results (shown as in Tab. 5-3) show that the probability of type II and III hazard level occurrence is highest in Shenzhen area. From this perspective, the results show that emergency management department should prepare corresponding emergency plans in advance to reduce the occurrence of secondary disasters.

According to the concept of dynamic probabilistic risk which is charactered by insufficient data dimensions, the proposed model applies information diffusion method to estimate the joint probability density, conditional probability density, and vulnerability surface (shown as Eq. 5-10, Eq. 5-11 and Eq. 5-16) with the comprehensive multiple hazards level, time data and multiple hazards losses. Results show that, on the one hand, the occurrence of hazard is more frequent in August. On the other hand, considering the occurrence of different hazard level for the same month, the probability of hazard level

I occurring in June and July is highest, and the hazard level II most occurs in August and October, and type III hazard level most likely to occur in September. These conclusions can guide emergency management department to prepare corresponding plans in advance to reduce the consumption of unnecessary resources. From the perspective of hazard losses, the direct economic losses caused by typhoons and rainstorms of the same hazard level in each month are different. The result indicates that the impacts of typhoons and rainstorms hazards on the economy are not the same. Besides, for the same month, the influence of economic loss decreases gradually when the hazard level degree rises. This result indicates that the capacity of rainstorm and typhoon hazards resistance in Shenzhen is reliable, and the ability to copy with the sudden hazard is relatively strong under the existing emergence system.

Finally, this research calculates the expected value of conditional probability distribution and vulnerability curve to quantify multiple hazards dynamic risk(shown as Eq. 5-17). The dynamic risk of typhoons and rainstorms hazards in Shenzhen region shows that the risk value of typhoon and rainstorm hazards in each month is different and the highest hazard risk value occurs in August and September. On average, the typhoons and rainstorms hazards bring the Shenzhen economy 114 million RMB and 167 million RMB losses respectively. From the above conclusions, it can be seen that these results are more in line with the actual situation and can give certain guidance of the emergency management in Shenzhen.

3. Future Work

Although the results obtained in this research are more in line with the actual situation, the proposed model can be improved. In future research, the following aspects can be considered. On one hand, the subjectiveness of weight calculation and the changes in interval attributes of the affected area for the vulnerability curve estimation have not been taken into account, so the corresponding methods can be studied in the future work. On the other hand, there are also some subjective issues regarding how to process the datasets for the case study, the adoption of a more scientific method to process the original data should be considered. The study of dynamic risk is a relatively new topic, in this research, it has been discussed from city scale and there are many works remaining to be solved.

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攻读硕士学位期间发表的论文及其他成果

(一) 发表的学术论文

[1] Gong, W., Chen, K., Huggins, T.J. and Yang, L.. Risk Evaluation Based on Variable Fuzzy Sets and Information Diffusion Method[J]. Journal of Applied Mathematics and Physics, 2020,8(5),821-830.(不为 EI、SCI 刊源，IF=0.58)

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