Environmental Risk Assessment for Sustainable Forest Management of Daxing'anling Area, China

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ABSTRACT

Though the forests of the world are vital for all humans, their area is decreasing. The elevating deforestation rate has a severe impact on the global climate as approximately 20% of the total human-induced greenhouse gas emission was caused by forest degradation and deforestation process. Furthermore, forests are the most species-rich ecosystems of the world and the advance of forest degradation and deforestation dramatically threatens their high biodiversity. To monitor and observe forest degradation, satellite based analysis is quite effective and often the only possible approach due to the vast and often inaccessible study areas.

The northeast China is the only remaining cold temperate forest area, which plays important ecological role on maintaining biological diversity and mitigating climate change. Additionally, the forestry industry has greatly supported the local economic development. However, the forest quality and quantity decreased dramatically over nearly 40 years of forest exploitation. Although the Chinese government has implemented forest conservation policies, the implementation of policies was not so effective because of the lack of knowledge on how to allocate the management resource. In this research, we aim to conduct an environmental risk assessment to help those decision makers for more effective policy implementation.

Taking advantage of remote sensing data on monitoring land cover change in a wide range area, we used the MODIS time series images to analyze the forest cover change and to extract areas influenced by forest fires from 2000 to 2010. Additionally, we defined the forest degradation as forest coverage decrease and compared that with forest burned area. Results showed that the forest fires were the main driving force of forest degradation and forest degradation mainly occurred in the eastern region of Daxing'anling.

Considering the uncertainty in forest fires occurrence, we used the environmental risk assessment theory to analyze the forest fires and its consequences. A forest fire is

a complex process affected by various factors. In this research, twelve variables related with climatic condition, topographical features and human activities were selected to predict the probability of forest fires occurrence. A weight of evidence model based on the priori probability obtained from historical data was established to identify the variables contributing for forest fires and a probability map of forest fires occurrence was generated. Result showed that the following ranges of factors significantly promoted forest fires: average wind speed (1.85–1.9 m/s), slope (0–6.26 °), river density (0–0.036 km/km^2), land cover (shrub land), population density (3.65–4.53 pop/km^2), and distance from residential areas (<2 km). In addition, forest fires frequently break out in the eastern part of the study area, which is close to human settlements. Forest fires occurred in zones identified as high susceptible by our model at a rate of approximately 87.5%, which indicated the effectiveness of our model.

In the environmental vulnerability assessment, thirteen variables related to exposure, sensitivity and adaptive capacity of the ecosystem were selected and integrated into a comprehensive index through spatial principal component analysis. The vulnerability within each part of the study area was then classified into five levels, including potential, slight, light, medium and heavy vulnerability, based on the numerical results. The degree of vulnerability was unevenly distributed throughout the Daxing’anling region. The highest environmental vulnerability index value was approximately 0.86 in the southern and central areas, suggesting that these regions are the most vulnerable to environmental changes. The lowest value was approximately 0.036 in the eastern region, which indicated a relatively high-quality environment that was less vulnerable to environmental changes.

Finally, a risk matrix approach was employed to combine the results of hazard (probability) and consequence (vulnerability) in the risk characterization stage. Fourth levels of environmental risk were regionalized for the whole study area. And result showed that the comprehensive environmental risk level is not so high across Daxing’anling since the high environmental risk area accounted for only 6% of total area. The majority of Daxing'anling area holds a potential or light environmental risk. The regionalization of environmental risk can used as a basis for decision makers to determine a prioritization in policy implementation, that more management resource should be allocate in the high environmental risk area while policies as prevention mechanism should be implemented in potential environmental risk area.

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LIST OF ABBREVIATIONS

Terms	**Explanations**
FAO	Food and agricultural organization
SFM	Sustainable forest management
IUCN	International union for conservation of nature
NFPP	Natural forest protection program
ITTO	The International Tropical Timber Organization
MCPFE	Ministerial Conference on the Protection of Forests in Europe
UN	United Nation
RIL	Reduced impact loggings
EC	European Communities
C&I	Criteria and Indicators
MPCI	Montreal Process Criteria and Indicators
MCDA	Multi-criteria decision analysis
DSS	Decision support systems
EIA	Environmental impact assessment
ERA	Environmental risk assessment
AEC	Atomic energy commission
WHO	World health organization
EPA	Environmental protection agency
MODIS	Moderate Resolution Imaging Spectroradiometer
EVI	Enhanced vegetation index
NDVI	Normalized difference of vegetation index
DEM	Digital elevation model
IGBP	International geosphere-biosphere programme
LAADS	Level-1 and Atmosphere Archive and Distribution System
WGS 84	World geodetic system 1984
HANTS	Harmonic analysis of time series
MODIS LST	MODIS land surface temperature
AVHRR	Advanced Very High Resolution Radiometer
HDF	Hierarchy Data Format
NBR	Normalized Burn Ratio

dNBR	Difference of Normalized Burn Ratio
CGIAR	Consultative Group for International Agricultural Research
WOE	Weight of evidence
Arc-SDM	Arc spatial data modeler
ROC	Receiver operating characteristic
AUC	Area under curve
IPCC	International panel of climate change
PCA	Principal component analysis
SPCA	Spatial principal component analysis
EVI	Environmental vulnerability index
AC	Adaptive capacity
NBC	Natural break classification

Chapter 1. Introduction

This chapter introduces the background of the research topic, which consists of two sections. The first section reviews the current research contents and progress on forest degradation and looks into the rationales for current research of environmental risk assessment theory. The second section identifies the main research problems in the research site. After that the main research questions in this research are addressed, the presentation of research contents and research objectives followed. Finally, the significance and limitation of this research were discussed and this chapter ends with illustrating its structure.

1.1 Background

As a main component of terrestrial ecosystem, the forest system plays an essential role on maintaining balance between the energy and substance. Moreover, forests provide human being with a broad range of goods and services (FAO, 2011). For instance, we have to acquire products like foods and fruits, medical plants and timber to support our livelihood. Meanwhile, forests act as a carbon sink to store more than 50 percent carbon dioxide in the atmosphere. Besides the direct value, forests also have other indirect values such as wildlife habitat provision, conservation of soil and water, and hydrological functions.

Nevertheless, with the development of economic and expansion of population, the forest ecosystem is facing a serious problem of degradation on a worldwide range. As reported by FAO (2010), the total area of forests in the world corresponded to over 4 billion hectares in 2010 which unevenly distributed in every country. In addition, primary forests which with no distinctly symptoms of human activity account for approximately 36 percent of the total forest area. In recent decades, due to various pressures imposed by natural and anthropogenic factors like extreme weather condition, biotic stress and tree species selection, harvesting regimes and natural disturbance, the forest resource in the tropical zone is decreasing at a dramatically high speed. According to the report proposed by FAO, about 104 million hectares of forest have been significantly affected by forest fires and pests (insects and diseases) or climatic abnormality like drought, snow and flood every year, resulted in 5.2 million hectares forest disappeared per year in a global level during 2000 to 2010 (FAO, 2010a). Meanwhile, afforestation and planted forest in some countries have substantially decreased the net loss of forest.

Forest ecosystem can provide multiple products and services which play a critical role to support local livelihood and protect the environment (Sloan & Pelletier, 2012), however, how to manage the forest in a way not to compromise future benefits is still a challenge in forest management. The majority of the world's forest, particularly in the tropical and subtropical area, are still managed in an unsustainable way (FAO, 2010b). Consequently, the concept of sustainable forest management has invented in order to protect the forest from deterioration (MacDicken et al., 2015). Sustainable forest management (SFM) was developed to address forest degradation and deforestation in a way taking the environmental, economic and social aspect into consideration (ICUN, 2009). In the environmental level, SFM aims to enhance the probability of forest to conserve soil and biodiversity and store carbon dioxide; as for the social aspect, SFM contributes to improve local livelihood and generate income (Leroy et al., 2014).

Although sustainable forest management has advantage on providing a wide range of ecological, economic and social benefit to society, uncertainty in forest ecosystem processes cannot be ignored which might affect the achievement of finable objectives. As well, some other processes like wildland fires (Shavit et al., 2013)and insect infestations (Rosenberger & Smith, 1997) can occur at a variety of temporal and spatial scales under different intensity levels. All this can be seemed as a source of great uncertainty for decision makers aimed to satisfy final objectives of sustainable forest management. This thesis will study the uncertainties come from forest fires and to identify the ecological vulnerable area in northeast China, which can be treated as a prioritization basis for sustainable forest management implementation.

1.2 Problem statement

1.2.1 Forest resource and forest change in China

According to the seventh national forest resource inventory report (2005-2009) (Lei, Westman, & Petry, 2009), the China's forest area covers 195 million hectares with the forest stocking volume at 13,721 million cubic meters, ranking fifth and seventh in the world respectively. In addition, the natural, historical and human factors lead to an imbalance between regional economic and social development, resulting in an uneven distribution of forest resource around the whole China (D. Li, Fan, He, & Yin, 2004). Most of the forests are located in the Northeast and Southwest area in which the total annual precipitation is above 400 mm, while the vast Northwest Territories and economically developed North China hold a small amount of forest resource (S. Li & Yang, 2000) (Fig 1.1.).

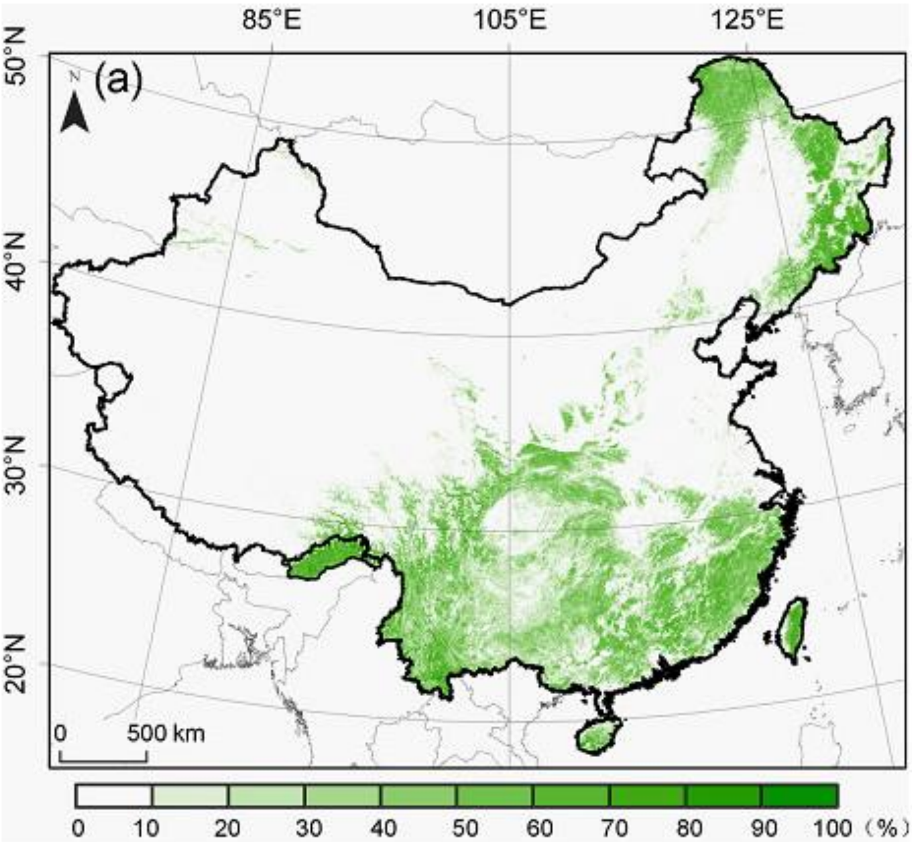


Fig 1. 1 The forest situation in China (Source: Forest resource inventory 2005-2009)

The different climatic condition and soil types lead to a very different distribution of forest type in north and south China (Li & Yang, 2000). The deciduous and coniferous forest system in Northeastern China was treated as one of the main timber supply area in where the stock volume is approximate 514 million cubic meters, simultaneously, this area holds rather unique ecological and environmental system in China (H. Xu, 1998; Y. Zhou, 1991) that function as a natural ecological screen for preventing the influence of Siberian cold air and a gene pool to conserve the biodiversity. The forest ecosystem in northeast China is one of the most ecologically fragile and economically under-developed region (Huang et al., 2010) and is particularly sensitive to change in temperature and other environmental conditions (Luo and Xue, 1995). Nevertheless, the management of forest resource went through a series of problems to date.

Since 1964, Chinese government implemented the regional development policy in northeast China to improve the economic condition, the forest here has been over-cut through a long period due to development of infrastructure and construction by the increased demand of wood products. In addition, the population growth also increased the demand for food which resulted in conversion from forest land to agricultural land. Moreover, the abundant foliage and dead branches under the dry weather condition makes this area easily be burned by forest fires (W. Yang et al., 2013). All these factors have led to a degradation on forest resource in the past 50 years in the Northeast China. Shi (2011) calculated the change in forest volume density and forest area at the provincial scale over the past three decades using the inventory data, as shown in figure 1.2, that forest density and forest area has increased in most provinces, above the diagonal line (red line in the figure), while, a decrease both in density and areas have found in the Ningxia and Heilongjiang province.

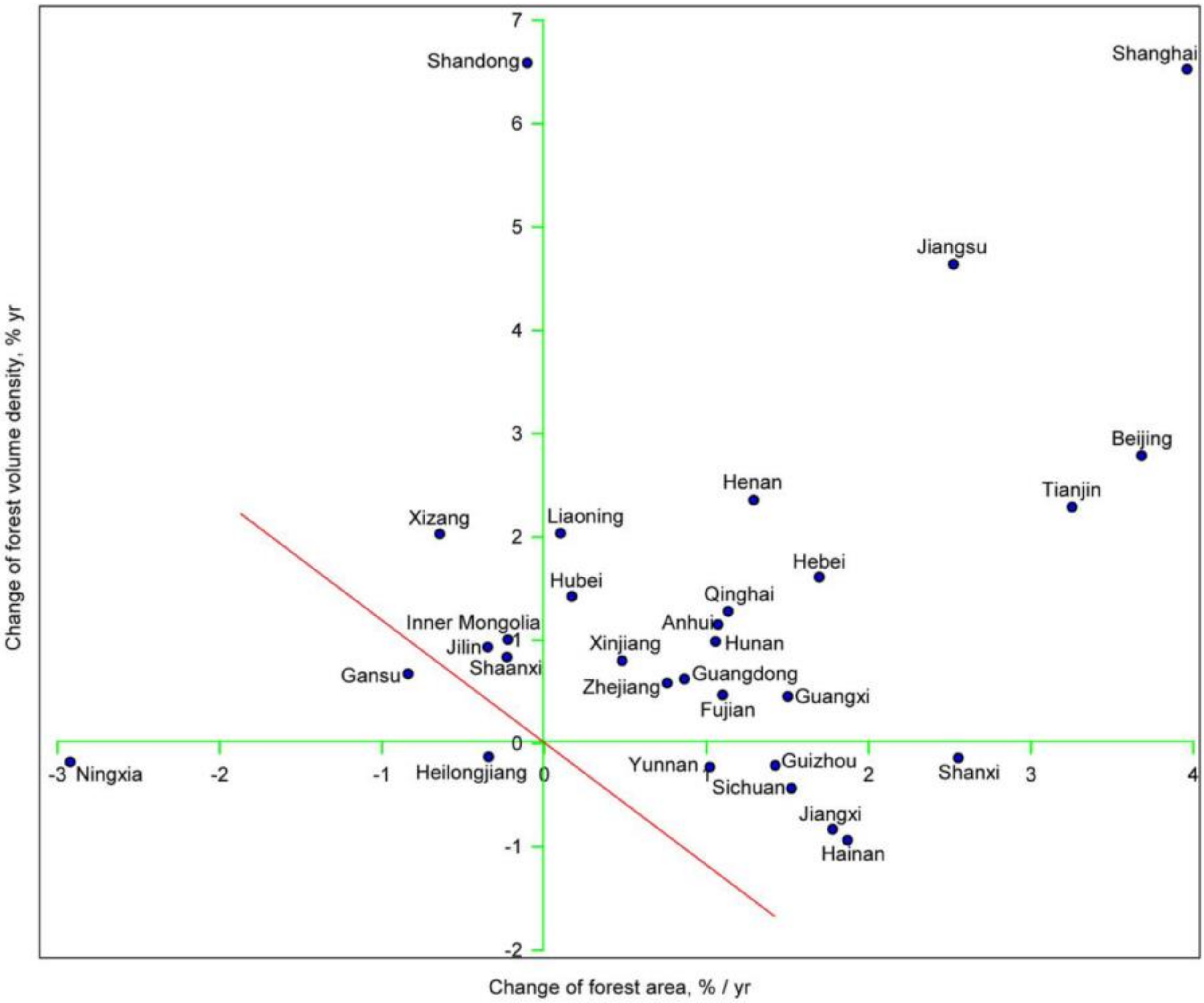


Fig 1. 2 The changes in China’s forests over the past three decades. (source: Shi et al., 2011)

1.2.2 Issues of forest degradation in Daxing’anling area

After about 50 year’s exploitation, the natural forest in Daxing’anling have undergone a qualitative change compared to the early stages of development, and the total standing stock volume has been decreased and the recoverable resource declined dramatically (Qi & Song, 2004). Moreover, the forest stand quality deteriorated due to the reduction of forest volume per unit area. As can be seen from Table 1.1, although the total forest area haven't change so substantially because of the afforestation, the live stocking volume and area of mature forest have decreased noticeably. The live stocking volume decreased approximate 28.8% from 720 million cubic meters in 1964 to 520 million cubic meters 2003, also the mature forest volume decreased 72.8% from 460 million to 120 million cubic meters. The ecological functions including carbon storage, water and soil conservation and biodiversity conservation have weakened due to the changes of forest land.

Table 1. 1 Changes on forest characteristic in Daxing'anling during 1964 to 2003 (data from the statistics bureau)

	Total forest area ($\times 10^4$ hm^2)	Live stocking volume ($\times 10^8$ m^3)	Mature forest volume ($\times 10^8$ m^3)
1964	840.1	7.2	4.6
2003	835	5.2	1.2

The forest ecosystem in northeast China is facing serious problems which are prominent contradictions for sustainable forest management process. Especially, natural forest is severely degraded and the quality of plantations remains low. In addition, the forest resource is irrational in structure. That means they have an excessively high percentage of timber forest and a comparatively low percentage of shelterbelt and economic forest. Meanwhile, the forest age structure is irrational as well, with the area of young and middle aged forest taking up over 70%, while the stock volume of mature and over-mature forest is on the decline. As a consequence, the harvestable forest resources are decreasing, and the harvest of middle and young forest stands would impose a great threat to the development of back-up forest resource.

The history of forest management in northeast China is not very far-reaching. It mainly went through three phases: natural regeneration (before 1964), intensive harvesting (1964 ~ 1998), and forest protection (1998 ~ until now). In the natural generation period, the human activity in this area is scarcely and the forest ecosystem is in virgin state with a high quality and a large quantity. The forest regeneration is mainly based on natural regeneration without human intervention. After 1964, the regional development requires more human and financial support. Therefore, a large amount of population was encouraged to immigrate into this area and a large area of forests were cut down for timber production. Conversely, the forest management system is lack to keep the balance between timber harvesting and tree growth. As a result, the forest system degraded dramatically during this period that the forest quality and quantity both decreased. In 1998, a huge flood disaster occurred in the three large river drainage areas of China (Yangtze River, Yellow River and the Songhuajiang and Nenjiang River), which caused enormous casualties and property losses. This disaster made the Chinese government realized the importance of environment. In 2001, the severe sand storm occurred in Beijing reinforced the determination of China's government to fight with deforestation and forest degradation. Therefor a series of forest management strategies have been developed to protect the environment especially the natural forest ecosystem, with the objectives to conserve biodiversity, protect water quality and prevent soil erosion and desertification. Among all the strategies, the Natural Forest Protection Program (NFPP) is the most recommended project to improve quality and quantity of forest ecosystem, which has been invested a large amount of financial resource.

The draft of NFPP was firstly published in October 1997, followed by implementation of several experimental programs. Through several discussion and revision, the implementation of NFPP was announced officially in December 2000. The NFPP program aimed at safeguarding China's forests through logging banning in natural forest area, subsiding afforestation and reforestation and a range of other policies.

Under NFPP program, several treatment have been implemented, such as establishing a special team of forestry police to enforce forest protection and restrain illegal cutting; redeploying and resettling state forest workers. Additionally, the central government invested a large amount of money to assist the workers who become unemployed because of the program (Yang, 2001). In most research, the NFPP was evaluated by physical indicators such as changes in harvested timber, newly planted woodland, which proved the implementation of NFPP has been successful. Timber harvests from natural forest area reduced approximately 50% from 1997 to 2000 (Ma, 2008). However, the implementation of NFPP have not been positive for all actors. Many of the smaller-scale enterprises with old equipment and inefficient management had to reduce or entirely cease production result of increased competitiveness and rise of raw material by NFPP. It caused a significant labor restructure that about two-thirds of timber production workers were unemployed by 2002 (Edstrom et al., 2012).

On the other hand, there is no clear guidelines about how to allocate the investments and which area should be prioritized for NFPP implementation. Consequently, the northeast China is facing serious problems with resources and ecological environment issues since sustainable development process has necessitated a special policy for forest sustainability. In order to ensure the sustainable development of forestry in this area, it is crucial to shift the focus of existing forest management and to propose effective policies to fulfil the sustainable forest management.

1.3 Research question

The following research questions are addressed in this study to propose some forest management policies in northeast China.

1) How have the forest cover changed during 2000 to 2010?

2) How can we detect the forest area affected by forest fires?

3) Is the probability of forest fires occurrence same among the whole area? How can we evaluate the probability of forest fires?

4) How can we quantify the potential impacts of forest degradation?

5) What kind of measurements can be proposed based on the results of risk assessment

of forest degradation?

6) How can we allocate the forest management resource effectively?

1.4 Research objectives and main contents

1.4.1 Research objectives

This research aims to conduct an environmental risk assessment for prioritization of existing forest management policies and to recommend some kind of risk management strategies to reduce the environmental risk value. In order to achieve this objective, this work envisages completing three sub-objectives:

(1) Detect forest degradation area during 2000 to 2010.

(2) Calculate the probability of forest fire occurrence.

(3) Identify the vulnerable areas based on the result of vulnerability assessment.

1.4.2 Research contents

This research conducted: 1) forest degradation monitoring; 2) probability prediction of forest degradation; 3) vulnerability evaluation of forest degradation; 4) integrated risk assessment of forest degradation; 5) risk management of forest degradation on the basis of environmental risk assessment theory.

In this study, we firstly monitored the forest cover change during 2000 to 2010 in study area by remote sensing data analysis. Meanwhile, the burned area of forest fires in the same period was extracted using the difference of Normalized Burn Ratio index. Through comparing the forest cover change area and forest fires burned area, the relationship of forest fires and forest degradation is determined. Additionally, risk assessment of forest degradation was conducted based on the application of environmental risk assessment theory, which defines that the risk was determined by the probability of hazardous event occurrence and potential loss caused by the event.

Combining the remote sensed data with field survey data, probability of forest fires was predicted using the weight of evidence method, a statistical method derived the contribution rate of each factor through analysis of historical data. Subsequently, the spatial principal component analysis was applied to evaluate the environmental vulnerability of forest degradation. Finally, integrating the hazard probability and environmental vulnerability, the comprehensive environmental risk assessment of forest degradation was conducted, based on which a series of forest management strategy was proposed.

1.5 Research method

In this research, the environmental risk assessment theory was introduced to analyze the uncertainty disturbance in forest management, which composed of three stages of problem formulation, hazard analysis and vulnerability assessment. The environment risk index can be calculated by multiplying probability of hazardous event and consequence together. Additionally, problem formulation is a preliminary characterization of hazard and consequences, as well as checking with scientific data and data availability, while the hazard analysis is the main stage to calculate the probability of hazard event and vulnerability assessment is to evaluate the potential consequence of the hazard event.

1.6 Scope of the study

This section presents the structure of this study. The whole dissertation consists of three main sections. The former three Chapters are the main problem formation stage that the early warning mechanism for risk mitigation is lack in the study site and additionally sustainable forest management should be implemented in order to keep the quality and quantity of forest resource. The middle three chapter is the key part in the whole research which is the basis for decision making.

This study consists of eight chapters. Chapter one gives an overall introduction of forest degradation, which is a serious issue in a worldwide range. This chapter also deals with the conceptualization of forest degradation from the perspective of forestry. In this study, forest degradation has been defined as the changes within the forest, which negatively affect the structure or function of the area, and thereby lower the capacity to supply products. It found that poverty and low land/man ratio coupled with consumerism trigger off series of events like logging, illegal felling. Apart from these, mining and oil and gas extraction due to ruthless motive for profit can be construed as main causes of global forest degradation. The main contents and objectives are determined here and the significance of limitation of this research is also pointed out.

Chapter two gives a geographic description of the study area and looks back the forest resource management process in Daxing'anling area during the latest decades. Also, the challenge and problems on forest management are identified through literature reviews.

Chapter three monitors the forest degradation situation in the past ten years and extracts burned area of forest fires in the same period by remote sensing data analysis. The results proved that the forest fires is the main stressor which leads to forest degradation in the study area.

Chapter four is hazard assessment in environmental risk assessment process. Here, a statistical approach called weight of evidence method is employed to predict the probability of forest fire occurrence.

Chapter five is vulnerability analysis stage which use the spatial principal component model to assess the vulnerability state of the whole study area and identify the vulnerable regions.

Chapter six is a comprehensive risk assessment part which combines the results of hazard assessment and vulnerability analysis. Also the sensitive analysis of the research is conducted in this chapter.

In chapter seven, the sustainable forest management policy is made, to proposed effective forest management strategy based on the result of comprehensive environmental risk assessment in chapter six. The whole study area is divided into regions with different levels of hazard status and vulnerability situation. And forest management treatments should vary among regions according to different risk level.

The dissertation ends by the chapter eight, which is the discussion and conclusion part. Here, the main results and finding is summarized and the future works and insufficient points are discussed.

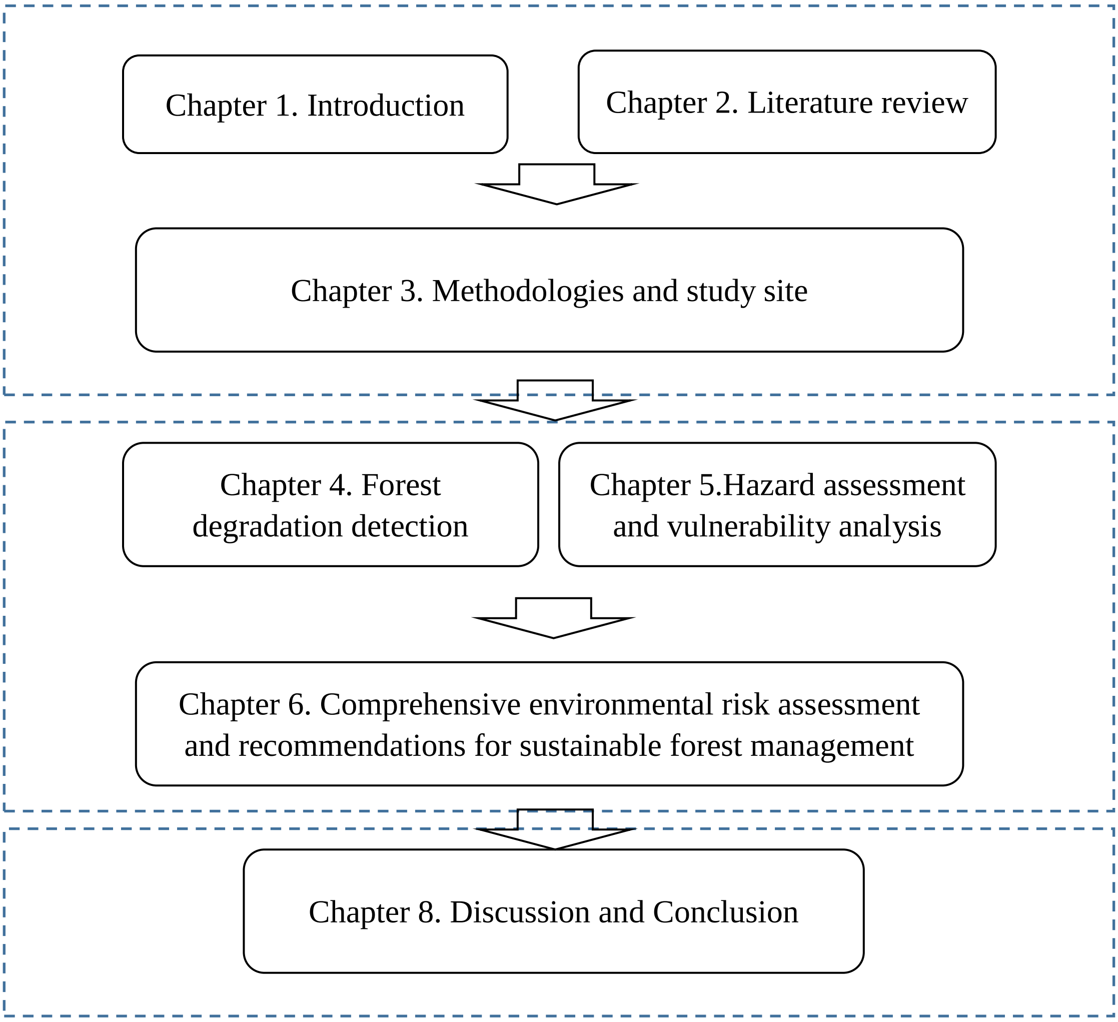


Fig 1. 3 Composition of dissertation

1.7 Significance of the study

This study attempts to propose a prioritization grade for carrying out the existing policy which aims to improve the effectiveness in practical implementation. On this ground, a series of treatments are recommended based on the results of environmental risk assessment. Since the forest degradation degree vary among different regions, the implementation of forest conservation treatment also should be implement at a different way. Here, the whole study area was classified into different risk region using a risk matrix approach, which can suggest the forest manager to implement a hierarchical management according to the environment risk level. On the other hand, this study introduced environmental risk assessment to identify variables lead to high probability of forest fires occurrence and heavy vulnerability, which can help decision makers to consider an oriented treatment for reducing the probability or improve the vulnerability. Moreover, this kind of environmental risk assessment have not been employed in the practical forest management process in the northeast China. Overall, this study aims to suggest suitable tactics to handle the problems in existing forest management policy in order to achieve sustainable management of forest resource.

Chapter 2 Literature Review

This chapter is a literature review part, including four main parts. First of all, researches related to forest management and sustainable forest management have been reviewed. Progresses made for sustainable forest management around the world were illustrated and problems in effectively managing forest resource were also pointed out through review. Then the literatures review about environmental impact assessment which is a common tool in decision making process were carried out to demonstrate the applications and issues in environmental impact assessment. Followed by the literature review of environmental risk assessment, which is a relative new tools for assessment of environmental situation. Finally, the current situation of forest management in Daxing'anling area was explained.

2.1 Forest management

Sustainable forest management is a concept related with forest degradation. As the forest degradation becomes to be a serious issue which might resulted in loss of ability to provide environmental goods and services, impose impact on local livelihoods and influence local and national development to some extent (Rober Nasi, 2011). Forest management strategies have been developed to prevent the exacerbation of forest degradation. Unsustainable forestry activities have already caused more than 850 million hectares of tropical forest degraded (ITTO, 2002), which might potentially affect millions of people whose livelihood depend wholly or part on forest goods and services at a local scale (FAO, 2011). By the beginning of twentieth century, approximate 90% of country's timber depended on imports – softwood from Baltic States, Russia and North America, and hardwood from tropical forest (Holmes, 1975). The increased demand for wood products and consequent growth in human population magnify the pressure on forest resource, and as a result, forest management mainly rely on timber primacy doctrine (Glück, 1987), which primarily assure timber production in qualitative and quantitative terms, and other functions such as carbon sequestration, protection towards natural hazards and tourism and recreation were overlooked in forest management process. It was the early stage of forest management lasting for many decades (Aletto & Ereno, 2008).

In the late 1990s, the demands on environmental and social function of forest ecosystem have changed and evolved over time, the sustainable forest management (SFM) appeared as a new forest management paradigm (Luckert & Williamson, 2005). It explicitly takes a broader range of forest goods and services into consideration than traditional forest management (Adamowicz & Veeman, 1998). Concerns over biodiversity, endangered species and degraded environments have sparked interest in managing forests. SFM emphasizes the final objective to keep balance between environmental, economic and social aspects of forest ecosystem by maintaining the health, integrity and biodiversity situation (Luckert & Williamson, 2005). The need for sustainably managing forest resource has been clearly articulated at the second Ministerial Conference on the Protection of Forests in Europe (MCPFE), and aroused the concern of European Forestry (Helsinki, 1993).

Pursuing sustainability has commonly become to be the main goal of forest management activities in the 21st century. Canada was the first country to hold an international seminar of expert on sustainable development of boreal and temperate forest in Montreal in 1993. This seminar aimed to establish a set of criteria and indicators to define and assess the progress towards sustainable forest management (Montreal Process Working Group 1998). After that, forest planning activities became more complex across Canada (Dunster, 1992) and the Canadian Forest Service began to treat sustainability as its mandate (Dunster, 1992). Sustainable forest management was defined on MCPFE as:

"sustainable management means the stewardship and use of forest and forest lands in a way, and at a rate, that maintains their biodiversity, productivity, regeneration capacity, vitality and their potential to fulfill, now and in the future, relevant ecological, economic and social functions at a local national and global levels, and that does not cause damage to other ecosystems" (Resolution H1 point D, MCPFE, 2000)

The underpinning principles of forest management have shifted from achieving production of single commodity (mainly timber) to sustained production of multiple goods and services that include maintaining future options and not damaging other ecosystems (UN,1992). Apart from the sustainably yielding forest products, the ecological, economic and social sustainability are also prospective to be considered into forest management (Aletto & Ereno, 2008). In recent years, various guidelines and tools have been developed at international, regional and national level on how to manage forest resource in a more biodiversity –friendly way (Dennis, Meijaard, Nasi, & Gustafsson, 2008). Especially in the Amazon area, on the context of large amount of conversion activities from forest land to cultivated land, a variety of forest management countermeasures have been practically applied to slow down the speed of forest degradation. Among them, the Reduced Impact Logging (RIL) (ITTO, 2007) was adopted as a main project to alleviate the influence of timber harvesting and illegal logging in the early 21 century (ITTO, 2000 http://www.itto.int/feature15/). Moreover, the RIL studies have been engaged in Southeast Asia (Elias et al., 2001), Africa and South and Central America.

Putz et al. (2008) reviewed the experimental results of RIL studies in different settings and compared the silviculture and financial impacts and elaborated that some aspects of RIL are lack of consideration such as protection of water course. Hasegawa et al. (2014) investigated the effects of reduced-impact logging and conventional selective logging practices on biodiversity and implied that the soil fauna community was strongly related with tree composition and the implementation of RIL mitigated the influence of loggings on decomposers of soil animals. Implementation of RIL might alter the regeneration species and the natural regeneration process was assessed in three different forest which harvested under RIL restriction in Eastern Amazon (Schwartz et al., 2017) and suggested that post silvicultural treatments and tending in logging gaps should be employed to guarantee the regeneration. Although RIL can sustainably reduce the undesired impacts of selective loggings (Putz et al., 2008), it might significantly affect tree generation. Therefore, approaches to minimize these effects should be employed in future management plans. Moreover, the guidelines of RIL vary among different countries and there is no universal set of RIL practices (Pinard, Putz, & Tay, 2000). Recent researches also clearly demonstrated that RIL techniques alone is unable to achieve sustainable forest management (Sist, Sheil, Kartawinata, & Priyadi, 2003).

For this reason, the SFM has been encouraged as an important guiding principle in managing forest resource (EC, 2003) to provide for today's needs under the premise not to damage the option of future generations (UN, 1992). Through discussion among participators in forest management in the past few years, the criteria and indicators (C&I) have been developed to guide SFM policies and planning (Brand, 1997; Keeton & Crow, 2009), which reflect a series of broadly aspects related to environmental, economic and social functions of forests. Since the application of C&I, it was treated as useful tool to collect and organize information which is helpful in conceptualizing, evaluating, communicating and implementing SFM (Prabhu et al., 1998). Variety of initiatives have been conducted for developing, testing and implementation of C&I for sustainable forest management (MPCI, 2009) at national level, sub-national level and forest management unit level. Additionally, the majority of C&I implementation was conducted at national level (Wijewardana, 2008). The Montreal Process (2009) provided a common framework to describe criteria and indicators of temperate and boreal forest area. And seven criteria and 67 indicators was determined through discussion between the 12 participating countries. Some research also tried to develop C&I at small scales. Jaliova et al., 2012 adopted a multi-criteria analysis approach to identify a set of C&I at field level and evaluate the management strategies in walnut-fruit forests of Kyrgyzstan and pointed that the forest health and vitality is the most important criteria in SFM. Multi-criteria decision analysis (MCDA) approach was proved to be effective for establishing and weighing the indicators through empirical preference ranking (Mendoza & Martins, 2003; Sheppard & Meitner, 2005). The decision support systems (DSS) is capable to integrate the decision maker's insights with computer's capability of information processing. However, only experts and stakeholder opinion was combined in DSS process, resulted in an excessive influence from stakeholder on weighting process. In C&I implementation, the procedure to weigh, aggregate and judge the threshold value of indicators is often not clear (Rametsteiner & Simula, 2003) which is inevitable for any forestry decisions (Kangas & Kangas, 2004). Lack of rigorous scientific information that can be applied in the decision making process has become to be a problem in addressing sustainable management.

2.2 Environmental impact assessment

Nowadays, environmental impact assessment has been employed as a primary tools for environmental protection and management around the world (Cashmore, 2004; Noble, 2009), which aims to inform environmental decision-making in the early stages of proposing plans to moderate the negative effects before development projects commence through evaluating possible environmental effects (Heinma & Põder, 2010). EIA process is intended to provide sound information to decision-makers, moreover, it was expanded to take account of broader environmental considerations in project selection and planning (Gibson, 2002). Possible impact was analyzed qualitatively for decision makers to decide whether to allow the project or not. The EIA is a process of identifying, predicting, evaluating and auditing environmental impacts (EC, 2012). Recently, the value of EIA has been recognized by practitioners (decision makers and stakeholders). It helps decision makers understand the possible impacts and make a decision (Norwich, 2013). However, the effective of EIA was doubtful whether it is capable to achieve the objectives of environmental management (Noble, 2009). Heinma and Põder (2010) employed the questionnaire to investigate the frequency of project implementation without EIA and indicated that a mandatory EIA requirement should be reconsidered when implement projects as well as make judgements. An EIA was conducted related to noise issues by Krukle (2012), and indicated that EIA process conduced barely accurately and treatment for noise reduction are insufficiently effective. Middle and Middle (2010) also concluded that the process of EIA is too long and costly was a constant theme, moreover the consideration to improve effectiveness is also important in EIA process.

Besides above issues, it is also not easy to make a decision even if decision makers got information through EIA, because many kinds of uncertainties and risks in different forms occurs in EIAs. Unsure about the knowledge is the main reason for these uncertainties (Stirling, 1999). To date, variety of studies pay attentions to uncertainty occurs in Environmental impact assessment, but the uncertainties are still a challenge in environmental impact assessment. Thissen and Agusdinata (2008) indicated that identifying and assessing uncertainties was not paid sufficient attention in environmental studies. In conformity with this, Maier and Ii (2008) also emphasized the importance of uncertainties during all stages of environmental decision making process. Walker et al. (2003) provided a conceptual basis for better communication among analysts by using uncertainty matrix tools and implied that understanding the dimension of uncertainty is a crucial step in decision support activities. Cardenas and Halman (2016) identified uncertainties involved in each decision making step and discussed a range of techniques to examine the extent of EIA guidelines in Colombia. Zhou (2015) proposed a conceptual framework incorporated into a Markov decision process model for uncertainties in forest carbon management, multiple forms of risk and uncertainty affecting forest function was analyzed, and the author pointed out that the stationary assumption and substantial costs limited the reliability of the forestation.

Until now, several different measurements and concepts about uncertainties has been developed for improvement of environmental impact assessment (Frias, 2015; Messier et al., 2016; Norwich, 2013; Tennǿy et al., 2006; Thissen & Agusdinata, 2008). Traditional method aims to reduce uncertainty empirically through modelling to better integrate known information (Frias, 2015; O’Hagan, 2012). Formal methods are to help optimal uncertainty information to make decisions (Cardenas & Halman, 2016; Messier et al., 2016). Through literature reviews, we can know that the integrated assessment is the most effective approach to solve the complexity of environmental problems.

2.3 Environmental Risk assessment

Probabilistic model is a way to conceptualize the level of uncertainty in a quantitative way, and the probability often known as likelihood of uncertainty. And the environmental risk assessment theory (Jones, 2001) is the most popular approach to address environmental issues incorporated into a probabilistic model. It is helpful to understand the relationship between stressors and environmental effects which is useful for environmental decision making (Hope, 2006). The structure of environmental risk assessment also can provides a common framework allowing the multiple stakeholders, regulatory groups and scientists to come to terms with the inherent difficulties of managing complex systems (Eduljee, 2000).

Risk based environmental assessment might be a potential tool to generalize and quantity environment system for environmental management which could provide basis to balance and compare risks associated with environmental hazards (Hunsaker & L.Graham, 1990). It can be used for exploring, explaining and forecasting the responses of an environmental system to changes in natural and human induced stressor (McIntosh et al., 2011; Whelan et al., 2014). In environmental risk assessment, uncertainties (probability of occurrence) concerning potential environmental effects (potential losses) are explicitly recognized and quantified if possible. A better perception of environment risks might be achieved through combining the magnitudes of uncertainties and the ultimate consequences.

Through the paradigm of risk assessment has been reported firstly by United States Atomic Energy Commission in their report of “Theoretical possibilities and consequence of major accidents in large nuclear power plants” (AEC, 1957), the risk assessment have made great progress and developed many approaches until now. The early stage is chemical pollution risk assessment (Lee-steere, 2009) of toxic substances which studies the ecological negative impacts of chemical pollutants. Lately in order to cope with information and uncertainties to understand the relationships between stressors and environmental effects (M. Fan, Thongsri, Axe, & Tyson, 2005), which is useful in environmental decision making, the risk assessment has transferred from qualitative analysis to quantitative evaluation (Eduljee, 2000). As the ecological function of environment has been realized important, (Barnthous & Suter, 1986) attempted to adapt the framework of human health assessment into ecological assessment. In the early 1990s, risk assessment was ultimately adopted as a management tool which has been applied to populations, communities and eventually to ecological landscape at large scales (Gormley et al., 2011). Environmental risk assessment theory has been successfully employed to address various kind of environmental problems such as vegetation degradation (Malet & Maquaire, 2008), climate change (WHO, 2014), and land degradation (Stankevich et al., 2016). However, the adoption of risk assessment as a formalized analytical process employed for environmental problems and latterly as a policy tool to help regulators in decision making is a relatively recent development (Eduljee, 2000).

2.4 Forest management in Northeast China

Northeast and Southwest China harbors the largest areas of forest land in contemporary China (H. Xu, 1998). The history of forest exploration in northeast is much shorter than eastern and southern part of the country (Xu, 2013). The natural environmental in the Northeast was almost pristine at the beginning of the Qing Dynasty (1644) (Wang et al., 2007), with a high level of quality. Only in the last century, this region has been fully explored and settled (Ye & Fang, 2009) and resulted in dramatic changes in forest cover and forest stock.

Three period of excessive timber harvesting can be witnessed in the past century (Yu et al., 2011). The first period was from 1896 to 1945, when this territory was controlled by Russia and Japan. The forest policy is harvesting without cultivation caused 18% of the forest area disappeared by the excessive harvesting (Ye & Fang, 2011). Then came with a period from 1950 to 1977 in which the main goal of forestry was produce economic value from timber harvesting (Zhou, 2006). During this period, the forest trees were clear cutting and artificial plantation was recommended. The third period stared from 1978 to 1998, the national economic reforms and broadening of international relations triggered deep and lasting changes in Chinese society (Wang et al., 2004), resulting with excessive loggings and no cultivation. This made the exploitable forest resource has been nearly exhausted in the region (Zhang et al., 2000). A substantial decrease of natural forests occurred in the meantime with serious degradation of overall forest quality and quantity. As a result, the ecosystem service provided by forest also change greatly, including soil erosion, biodiversity decline and carbon dioxide emission (P. Zhang et al., 2000), which weakened the capacity for sustainable economic development (Zhou, 2006).

In 1998, floods in the Yangtze River basin was an alarm for Chinese government to recognize the importance of environmental protection (Zong & Chen, 2000). In response, Chinese government shifted the focus of forest management from simple wood production to policy adopting ecological restoration and protection (Yu et al., 2011). The most striking one is the Natural Forest Protection Program (NFPP), and then the timber harvesting has decreased and forest areas and stockings have increased slowly (Wang et al., 2004). However, how to select management models and strategies to best protect, restore and manage forest land in such a large area is still a challenges for researchers and decision makers in China.

The State Council committed 96 billion yuan to finance the first phase of NPFF program from 2000 to 2010. Much of this investment was expended as subsidies for forest enterprises (Xu et al., 2002). According to State Forestry Administration, approximately 60% of central government subsidies to the policy implemented area were spent as employment costs for state forest enterprise (Xu et al., 2006). The major changes about harvesting activities caused significant reformation of labor structure. By the end of 2002, approximately two-third workers had left their workplace (Edstrom et al., 2012). From the aspect of increasing forest area and decreasing harvested timber, the NFPP can be considered to be successful (Ma, 2011). However, in the implementation, some kind of socio-economic effects of NFPP was unexpected, such as some unforeseen influence on local economics (Cohen et al., 2002). Shen et al., (2006) concluded that although the NFPP program has been effective in decreasing harvesting, impacts on household livelihoods was found negative. The labor restructure led to an income reduction for a range of people, meanwhile, the revenue of local government has also greatly decreased because of loss of income from loggings (Xu et al., 2006).

On the other hand, although huge amount of funds were invested for NFPP, the rule of how to allocate the money was not clearly. The vast majority of the investment was mainly spend on compensation for worker who has lost their job due to NFPP (Y. Yang, 2001). For plantation and tending activities, the Chinese government instituted a uniform standard to financially support NFPP (Zhu, 2012). However, the actual situation of forest ecosystem varies among different areas, which means the investment also should be correspond with the actual situation. In the previous studies, the part of area has the prioritization for NFPP implementation wasn’t articulated.

In this research, the environmental risk assessment (ERA) was employed to provide information about the environmental situation, which is helpful for decision makers to implement sustainable forest management. The ERA has advantage to deal with uncertainties occurred in forest management due to forest fires. Moreover, it can give a priority consideration for regions has a high environmental risk level, which is able to improve the efficiency of sustainable forest management.

Chapter 3 Methodology

This illustrate the methods used and process involved in order to achieve the objectives of this study. The practical framework of Environmental risk assessment which is suitable for the regional case is explored. Followed by a detailed natural situation depiction of study area. Then an explanation in data needed and data collection was introduced. This chapter is ended with a data processing framework in the whole research.

3.1 Environment risk assessment

Environmental risk assessment was defined as “evaluate the likelihood probability of adverse environmental consequence which occurring as a result of exposure to one or more stressors related to natural disturbances and human activities” (EPA, 1992). It is an approach to systematically evaluate and analyze data, information, assumptions and uncertainties in decision making process (EPA, 1998).

3.1.1 Theory of Environmental risk assessment

Environmental risk assessment is a new study field accompanied by a shift on objective and concept of environmental management (Fu and Xu, 2001). Since the 1970s, weakness of zero risk of environmental management in some industrialized countries is gradually exposed in the society, therefore risk management, a new environmental policy was generated in the early of 1980s. The risk management focuses on balance of risk grade and reduction of risk costs, which is aim to understand the relationship between risk level and risk acceptable by general society. Through 20 years’ development, the evaluation content, scope and method have been improved greatly. It focused on one chemical and one receptor. Currently, it is mainly applied to large spatial and temporal scale targets (Landis, 2003). In order to address complicate environmental problems, environmental risk assessment is used to systematically assess and cope with information and uncertainties to understand the relationships between stressors and environmental effects (M. Fan et al., 2005).

The distinctive nature of environmental risk assessment framework derived mainly from three different emphasis compared with previous risk assessment approaches (such as human health risk assessment). On the first hand, environmental risk assessment consider effects which might examine population, community and ecosystem impacts. Second, no agreement on assessment endpoint which means no one set of endpoint can be generally applied, they were selected from a very large number of possibilities based on scientific and policy consideration. Finally, a comprehensive environmental risk assessment might go beyond the traditional emphasis on one chemical effects and consider the possible effects of non-chemical stressors.

The framework of environmental risk assessment is shown in figure below. The whole process is based on two major phases: characterization of hazard (probability) and characterization of environmental consequences (potential loss). Although these two phases are most prominent in the analysis process, aspects of both hazard and consequences are considered through problem formulation, as shown by the arrows in the figure. The analysis process also contains the risk characterization step, in where the hazard and consequences are integrated together to evaluate risk. This framework referred to the Environmental Protection Agency (EPA) paradigm for ecological risk assessment (EPA, 1992).

It introduce the process of environmental risk assessment as follows:

Firstly, environmental risk assessment started from problem formulation, which includes a preliminary characterization of hazard and consequences, as well as checking with scientific data and data availability, site-specific factors to decide the feasibility, objective of whole environmental risk assessment. Because environmental risk assessment needs to address risks of stressors to many components as negative impacts, problem formulation might provide an early identification of key factors which should to be considered, and produce a more scientifically sound risk assessment.

Secondly, the framework consists of two activities, characterization of hazard and characterization of vulnerability. In hazard analysis, we aims to predict or evaluate the spatial and temporal distribution of a stressor and its occurrence probability, while the purpose of vulnerability analysis is to identify and quantify the negative influences elicited by the stressor.

Risk characterization is the final phase of the framework. It combines the results of hazard analysis and vulnerability evaluation to assess the likelihood of adverse environmental effects associated with susceptibility to a stressor. The ecological significance of risk characterization is on the consideration of the types and magnitudes of the effects, their temporal and spatial distributions and the likelihood for recovery.

Figure 3.1 indicates that discussion between risk assessor and risk manager is indispensable in the framework, because the risk manager is able to help ensure what kind of information is relevant to making decisions on the problems under consideration. Also, a role for verification and monitoring can help to make sure the overall effectiveness of the approach and provide necessary feedbacks thinking about the future modification for the framework.

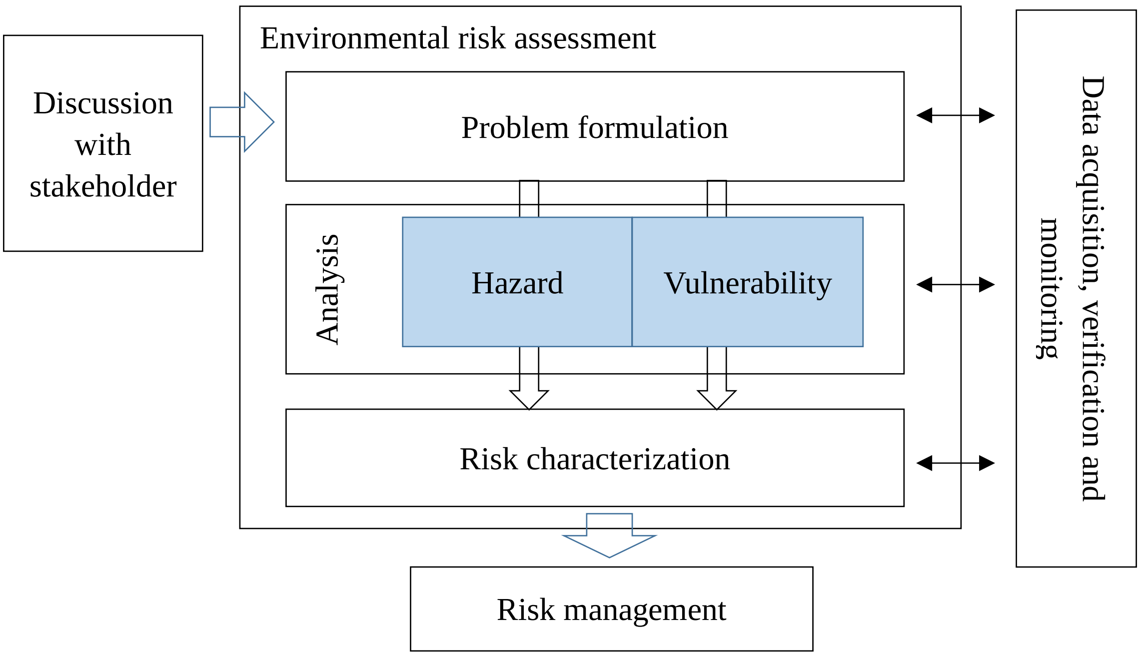


Fig 3. 1 Framework for environmental risk assessment (referred to EPA, 1992)

3.1.2 Advantage of environmental risk assessment

Environmental risk assessment has several advantages as applied to environmental planning and management. It can provide a quantitative basis for comparing and prioritizing risks. In the risk assessment process, the probability that an adverse outcome might happen was characterized as a result of exposure to the stressors. By showing the results as probabilities, it enable to recognize the inherent uncertainty in predicting future environment states, which makes the assessment more credible.

3.2 Study site

3.2.1 Location

Daxing’anling area is located in the northwestern part of Heilongjiang province, northeast of Inner Mongolia Autonomous Region, situated in the northeastern slope of Daxing’anling Mountains (Figure 3.2). This area has a latitude range from 50°10’ to 53°33’N, and a longitude range from 121°12’ to 127°00’E, covered a total area of 840 km^2, occupies 0.9% of total China. The administrative region of Daxing’anling crosses two province of Heilongjiang and Inner Mongolia. The precinct includes three counties of Huma, Tahe, Mohe and two districts of Huzhong and Xinlin.

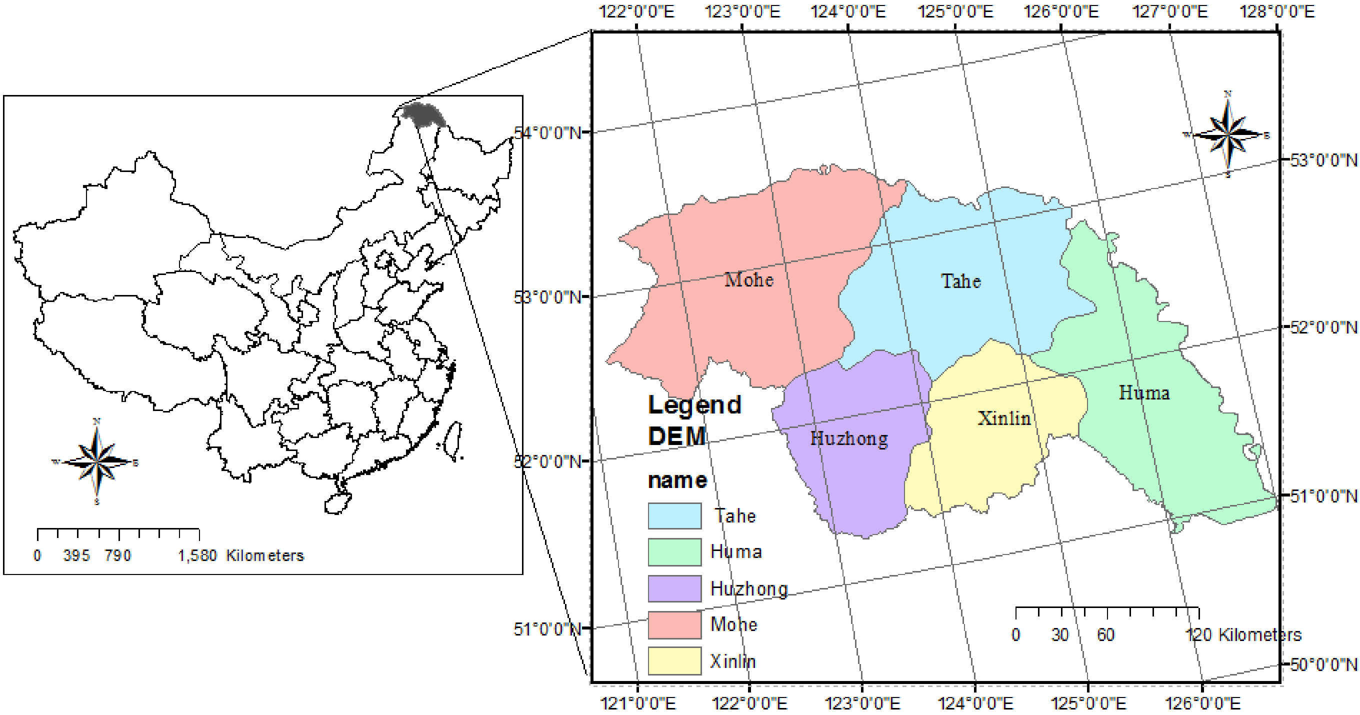


Fig 3. 2 Location map of Daxing'anling area

3.2.2 Mountains and topography

The topography in Daxing'anling region is a kind of folded mountains, which was formed by the joint action of platform depression area and geo-synclinal fold uplift area (Tao et al., 2014). After a long geological evolution history, the main mountain range extended many branch mountains along both side and countless long slow side ridges (Sun, 2010). The overall topography appears that it is lower in west and higher in lower in west and higher in east (Fig 3.3). The highest peak has an attitude of 1509 meter, which is located in the intersection of Daxing'anling ridge and Yilehuli Mountain. While the lowest point is at Yanjiang village with value of 134m. According to elevation, the study area can be divided into shallow hill, hill, Low Mountain and Middle Mountain from east to west.

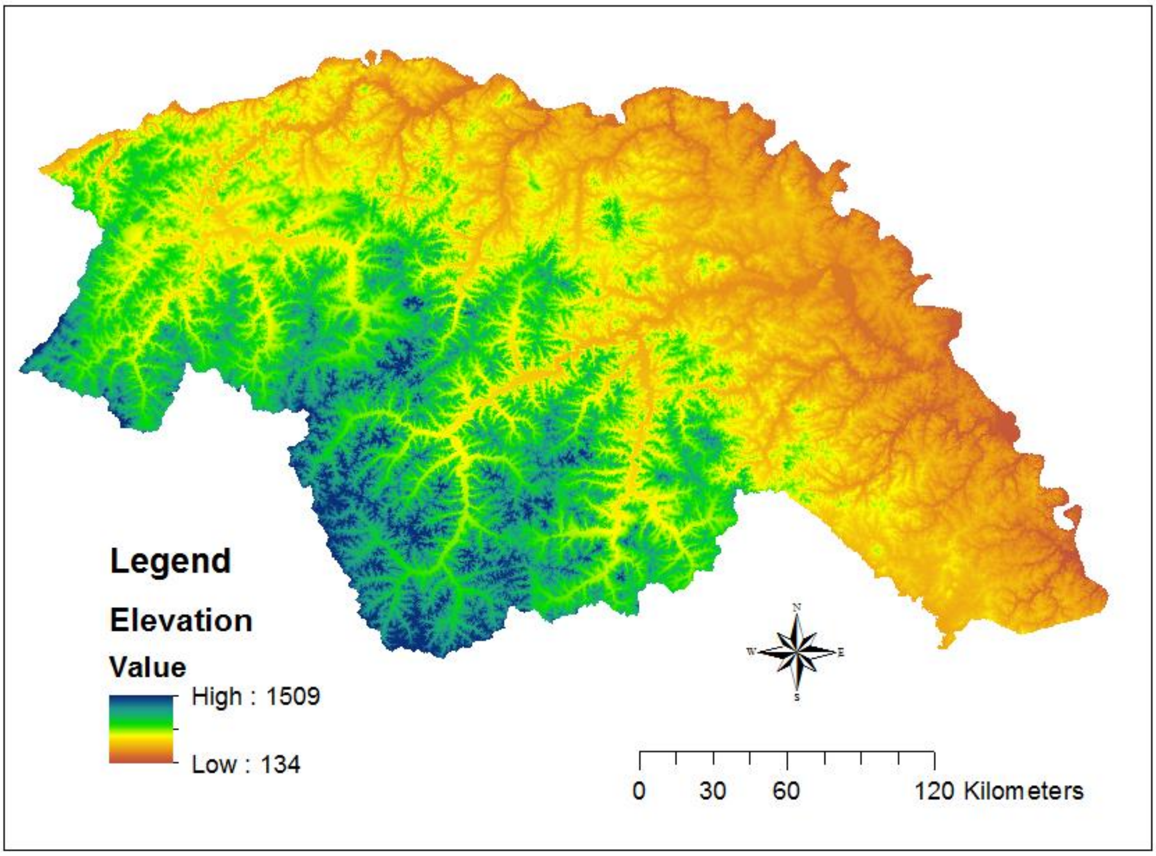


Fig 3. 3 Elevation distribution in study area

The rivers is flowing all over the region, therefore, the water resource is abundant. Due to the presence of permafrost soil and seasonal frozen layer, the action of river decline is blocked and the lateral erosion of river is increased, as a consequence, the valley in Daxing'anling area is broad.

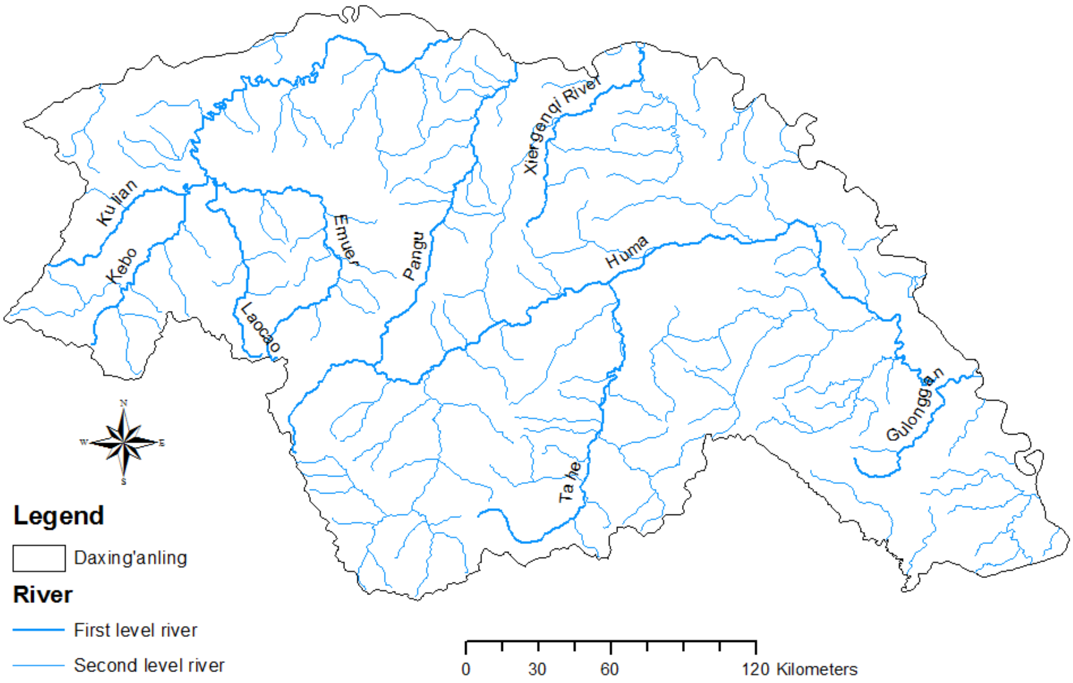


Fig 3. 4 Water system in study area

In addition, because the river is broad and flat, the precipitation discharge is slow so that the area of frozen soil layer expands and it result in poor soil permeability that lead to most water retained in the surface. There are 178 rivers, and their total watershed area is wider than 50 square kilometer. The water system can be classified into Heilongjiang and Nenjiang (Table 3.1).

Table 3. 1 The statistics of river resource in Daxing'anling area

Water system	Name of river	Watershed area (km^2)	Average annual flow (m^3/s)	Total length (km)	Natural river fall (m)
Heilongjiang	Humahe	31210	215	524	740
Heilongjiang	Emuerhe	16280	92	469	761
Nenjiang	Duobukuer	5490	39.1	278	635
Heilongjiang	Panguhe	3638	218	133	367
Heilongjiang	Xiergenqihe	3858	21.8	133	367
Nenjiang	Ganhe	19549	129	447	726

(Source: Administrative Water department in Daxing'anling area)

3.2. 3 Climatic characteristics

The Daxing'anling area was controlled by the temperate continental monsoon climate with obvious features of mountain climate (Fig 3.5 and Fig 3.6). The seasonal temperature varies significantly. The spring starts from late April to late June with changeable weather soon that the temperature rises sharply. The summer begins from June to August with high temperature and high precipitation. The autumn is from August to October with low temperature and dry weather. The winter is the longest in the study area which lasts about half of the year from October to April. In winter, it is very cold with great amount of accumulated snow.

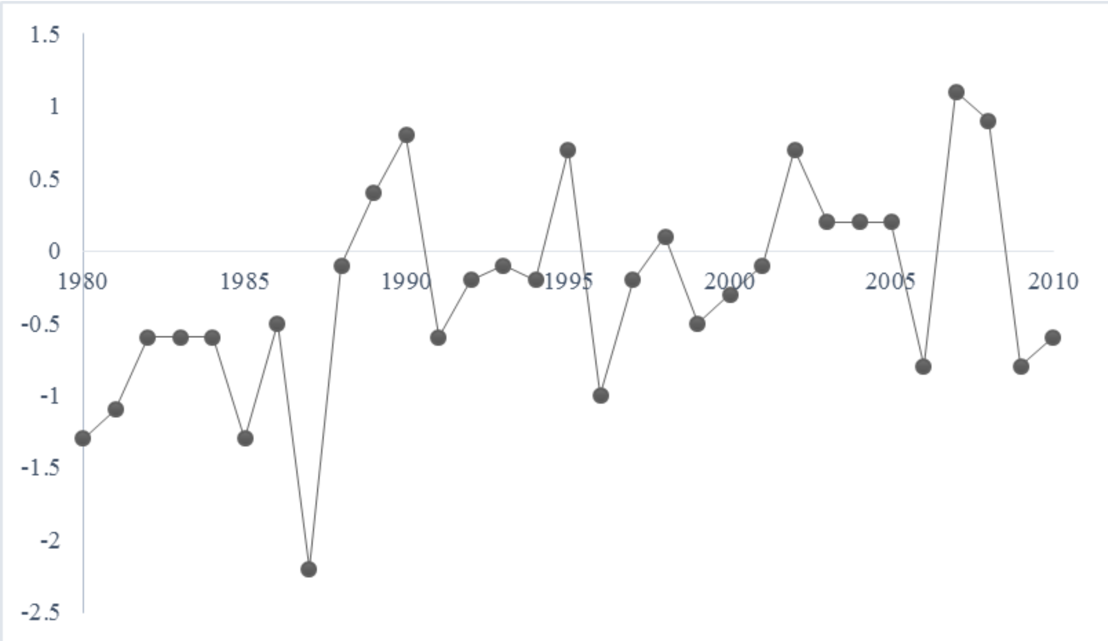


Fig 3. 5 Trend of annual average temperature from 1980 to 2010

According to the historical statistical data, the annual average temperature is about -0.8℃ to -4.3℃, the extreme minimum temperature was recorded in Mohe in February 13th 1969 with the value of -52.3℃, while the extreme maximum temperature was recorded in Huma in July 18th 1994 with the value of 39.4℃. The total annual precipitation is about 400~500mm with uneven distribution in temporal and spatial scale. Generally speaking, the northern and eastern part is lack of rainfall while the central and southern part is rich of precipitation. In addition, almost 70% of precipitation fall in summer, whereas rainfall in winter accounts for only about 10% of annual precipitation.

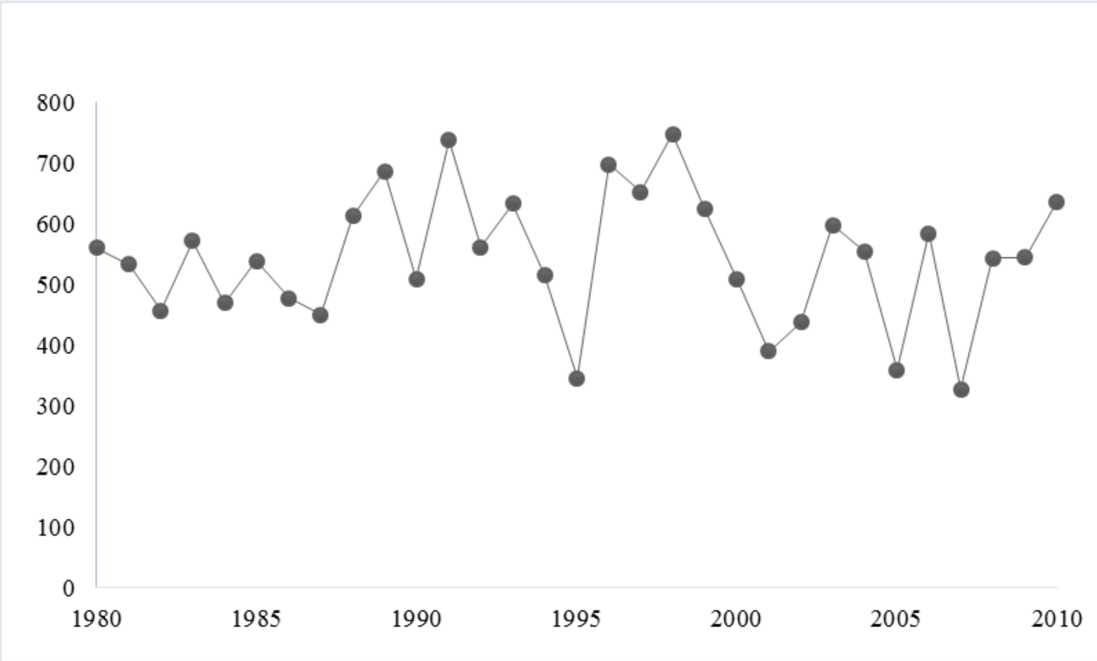


Fig 3. 6 Trend of annual total precipitation from 1980 to 2010

3.2.4 Soil characteristic

The soil type is classified into brown coniferous forest soil, dark brown soil, gray forest soil, meadow soil and swamp soil. Among them, the brown coniferous forest soil occupies a large proportion and is seemed as the representative soil type in Daxing’anling area. Its formation is not only related with the climate characteristics, geological rock and vegetation condition, but also closely associated with the permafrost soil layer. In other word, the permafrost soil is an important characteristic of brown coniferous forest soil, meanwhile, it is a critical forming condition of brown coniferous forest soil. This kind of soil is covered by the larch forest mixed with Scotch pine and birch trees. The soil layer is relatively thin in the whole study area (20-40cm), contains more gravel particles of which the podsolization is not so strong. The surface layer is thin with low fertility and the humus content is about 10%~30%.

3.2.5 Vegetation characteristic

According to the vegetation regionalization of China, the study area belongs to cold temperate boreal forests, which are the southward extending section of Eurasian coniferous forest (Y. Zhou, 1991). Woodland area accounts for a large proportion with a total area of 6.65 million ha, and vegetation coverage is approximately 79.83% (2010 forestry inventory). The canopy species composition is relatively simple, dominated by larch (Larix *gemelinii*) and pine (Pinus sylvestris var. *mongolica*), mixed with birch (Betula platyphylla) and spruce (Picea *koraiensis*). According to the altitude, the forest can be divided into different subclasses. Herbage-Larix gemelinii forest range from 350-750m, Mongolian oak-larch forest ecosystem located in the southeastern part with lower elevation than 450m, Spruce-larch forest located in the higher elevations, in the approximate range of 820-1100m.

Fig 3. 7 The situation of forest coverage in Daxing'anling (Photo at 21 July 2015)

The forest in Daxing'anling area is one of the main area of natural forest in China, Meanwhile, it is the only exist boreal forest around China. Because of the special geographical location and natural climatic conditions, there are still intact natural forest ecosystem and wetland preserved in this region, which contains the only remaining boreal biodiversity system in China.

3.3 Dataset

3.3.1 Data need and data collection

Forest fires play an important role as a forest landscapes shaping agent (Cissel et al. 1999; Seymour et al. 2002; Cleland et al. 2004; Nitschke 2005), which are indispensable factor in vegetation succession. As pointed by Ruokolainen & Salo (2009) forest fires have positive effect on biodiversity to some extent, however large and frequent occurrence of forest fires might negative affect carbon stocks (Ilvestrini et al., 2011) and decrease the capacity of soil and water conservation (Farshad et al., 2004), since it can wipe out all vegetation and release large amounts of carbon dioxide (Dokas *et al.* 2007). Historically, the Daxing'anling is a fire-prone areas. According to the Chinese National Bureau of Statistics, more than 10 million hectares of Chinese forest have been affected by forest fires during the past 50 years (Gao 1999). Living trees above hundred year with fire burns can be seen everywhere, and charred interlayer in ground soil was often observed when doing soil profile. The dry cold weather condition and strong winds in northern Daxing'anling makes this area easily to be burned by forest fires, meanwhile, accumulation of leaf litter for many years lead to an increase of combustible materials. In addition, the tall standing wither-bark is the main reason of lightning fires in this area.

According to the local government statistical data, the total numbers of forest fire in Daxing'anling area reached 1561 times from 1966 to 2010, about 36 times per year. The total burnt area is about 6.6×10^4 km^2 in the 43 years (Fig 3.8). And recently it seems that the occurrence of forest fires are becoming more frequent.

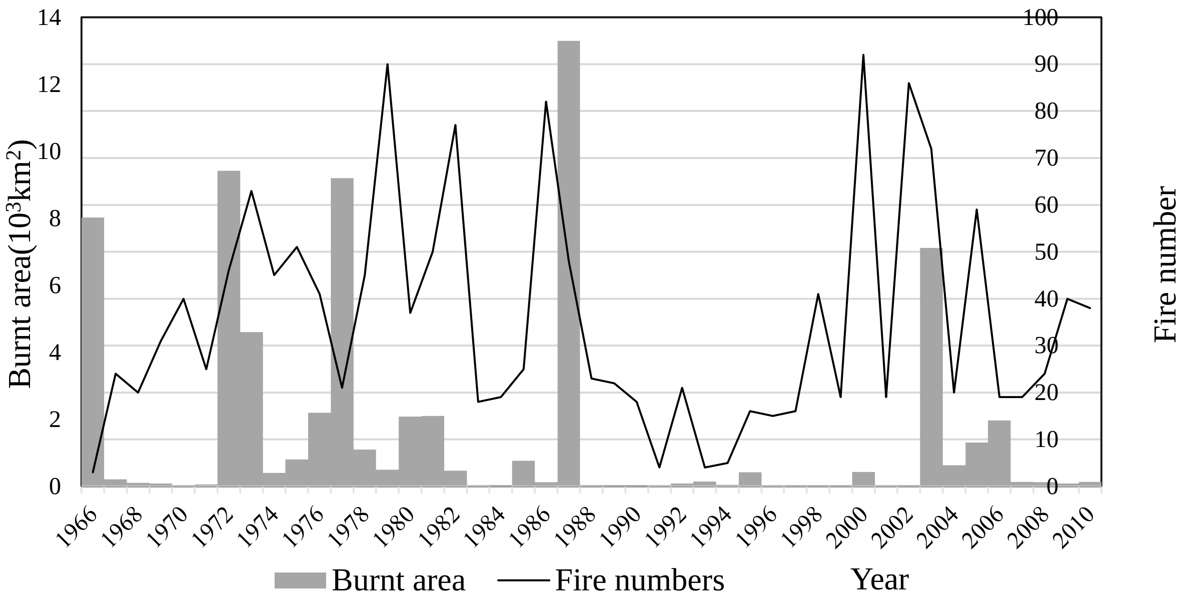


Fig 3. 8 Annual forest fire occurrence from 1966 to 2010 in Daxing'anling area

Obviously, forest fire can be treated as a disturbance event which contributed greatly to the forest degradation process in this area. Moreover, due to the natural forest protection program, the volume of timber harvesting has been decreased during 2000 to 2010. Therefore, in this research, we have a fundamental assumption that forest fires are the hazard event which might cause unpredictable potential losses to other related ecosystems such as atmosphere, hydrosphere, biosphere and human livings.

In this research, the remote sensed dataset Moderate Resolution Imaging Spectroradiometer (MODIS) was mainly used to classify the land cover and extract the forest fire burned area in Daxing'anling. The Terra/Aqua composite 16-day global 250m MODIS atmospherically-corrected dataset (MOD13Q1) was used to extract the vegetation indices of enhanced vegetation index (EVI). Land surface temperature was derived from composite 8-day global 1km MOD11A2 time series dataset. Additionally, atmospherically corrected level 3 8 day composite surface reflectance data (MOD09Q1) and active fire product derived from MOD14/MYD14 product with a global coverage and 1km spatial resolution was also employed to forest fire analysis. The detailed data processing can be seen at each chapter.

Apart from remote sensed images, other source of ancillary data also have been used in this research as followed:

Table 3. 2 Ancillary data used in this research

Data	Usage	Source	Description
Digital elevation model	To extract topographical variables such as elevation, slope gradient and slope aspect	Freely download from Geospatial data cloud: http://www.gscloud.cn/sources/?cdataid=302&pdataid=10	Shuttle Radar Topography Mission with path number of 61 and row of 2. The spatial resolution is 90m.
Plant functional map	To help identify the geographical distribution of Chinese vegetation	Obtained from Cold and Arid Regions Science Data Center at Lanzhou (Ran & Li, 2011)	A functional classification of Chinese vegetation at 1km
Weather condition	To obtain climatic data of temperature, humidity, wind speed and precipitation.	Supported by China meteorological data sharing center: http://data.cma.cn/	Records of five weather station were interpolated using Ordinary Kriging.
Demographical data	To understand the social situation of the study site	Derived from the Daxing'anling statistics Bureau	Including demographic and economic data

A field survey was carried out at 17 July 2015, which aimed to get sampling data for land cover classification and to collect forest inventory data through consulting with the local Daxing'anling administrative government.

3.3.2 Data processing

In this research, the data processing contains four main parts. Firstly, remote sensing data including MODIS time series vegetation index product and Landsat 5 image coving the study area combined with forest inventory data was employed to classify the forest cover types, then the forest cover change from 2000 to 2010 was detected through overlapping the classification at this two period. Secondly, MODIS surface reflection data and forest inventory data were used to extract the burnt area of forest fires in the same period. This two parts were seemed as hazard identification stage, which proved that the forest fires are the main driving force of forest degradation in Daxing'anling area. Then, in the hazard analysis part, weather condition data, topography data and demography data were applied to mapping the probability of forest fires occurrence. Finally, forest inventory data and demographical data were used to analysis the environmental vulnerability status of the total study area. The detailed flowchart of data processing was showed as Fig 3.9.

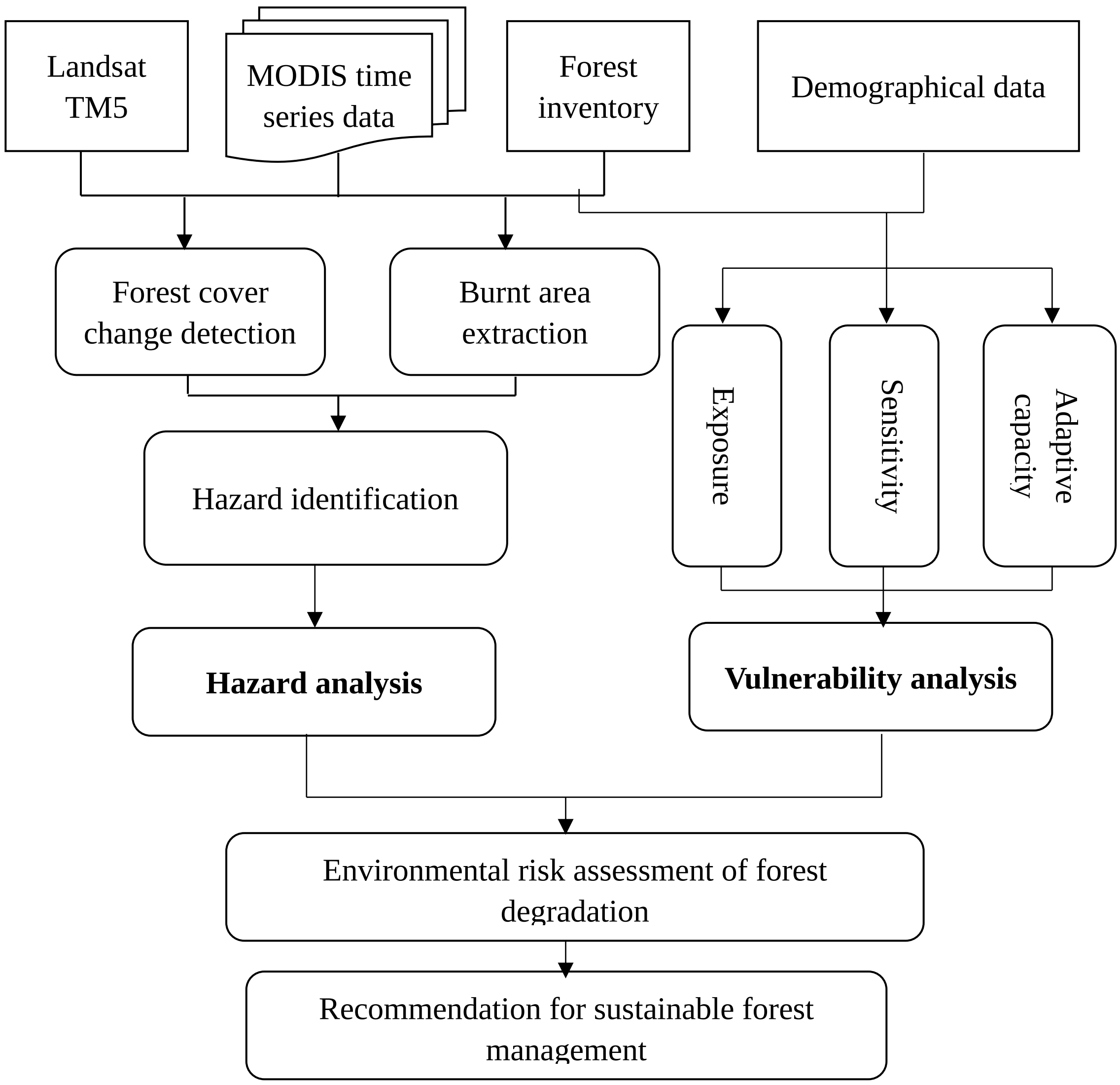


Fig 3. 9 Flowchart of data processing

Chapter 4 Identification of forest degradation

This chapter attempt to identify the hazard event resulted in forest degradation. As an important part of environmental risk assessment, hazard identification is always carried out through problem formulation, which provides the original descriptions of the ecological system and is a systematic planning step to determine the major steps in the environmental risk assessment process. In this chapter, the land cover classification across broad spatial range was conducted by using remote sensed images and forest cover change during 2000 to 2010 was detected. On the other hand, the burned area at the same period caused by forest fires also extracted by applying the spectral index difference. In order to prove that the forest fires is the main cause of forest degradation, the two kind of maps were overlapped in ArcGIS.

4.1 Classification of forest cover change

Understanding the situation of forest degradation is fundamental for the sustainable forest management(Davidar et al., 2010). In the past times, the detection of forest change in China is mainly relied on the forest inventory which cost time and money. Since the remote sensing data can meet the data demand among a large temporal and spatial scale, it has become one of the most commonly used techniques around the world and it has been successfully applied to land type classification (Baroudy, 2011; Grinand et al., 2013). Generally, these techniques can be divided into either data mining or statistically based procedures, depending on the assumptions of the model and the way to conduct the model (Hogland, Billor, & Anderson, 2013). In the discriminant analysis such as maximum likelihood classification might overestimate the magnitude of association among classes (Hosmer & Lemeshow, 2000) and produces misleading posterior probabilities if assumptions are not satisfy (Johnson & Wichern, 2007). In order to address these issues, a number of different techniques have been applied to develop many classifiers, and results might vary among different classifier (Lu et al., 2004). In contrast, among the data mining methodologies, decision trees, neural networks, and K-means clustering have been developed to be quite popular (D. Lu & Weng, 2007). Especially for the decision tree classification method, it might be better suited to the situations where a single cover type is represented more than remote sensing features because it is not rely on any assumptions of normality within training area (DeFries, Hansen, Townshend, & Sohlberg, 1998).

The vegetation indices have advantage in providing consistent, spatial and temporal comparison of vegetation condition (Justice et al., 1998). Normalized Difference of Vegetation Index (NDVI) has been widely used in land cover classification and change detection and monitoring(Goward et al., 1991; Tucker et al., 1985). However, NDVI is easily to get saturation in high vegetation cover area (B. Matsushita, et al.,2007). In this paper, Daxing'anling forest is the study site, where the land was densely covered by forest trees. Therefore, in order to improve the sensitivity in high biomass region(Huete et al., 2002), the enhanced vegetation index (EVI) was chosen to identify the phenology characteristic of vegetation. Although higher resolution data such as SPOT and IKONOS can provide valuable information about vegetation cover, they are difficult to apply for large areas based on the current regional land cover classification (Lu et al., 2004) in practical applications. The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board Terra and Aqua satellites after launch in December 1999 and May 2002 have been used in monitoring land surface changes continuously in space and time due to this multi-year and long-term time series images (Mildrexler et al., 2007; Hansen et al., 2008). Moreover, the MODIS data also has been applied to examine the ecological functions of vegetation dynamics for various purpose (Bucha et al., 2008; Setiawan et al., 2011).

In this research, the phenology feature of vegetation derived from the MODIS EVI data, land surface temperature extracted from MODIS LST data and topographical characteristic calculated from digital elevation model (DEM) was treated as input data to establish a decision tree model, a non-parametric and hierarchical classifier. It predicts land covers through recursively partitioning a data set into more homogeneous subsets (Quinlan, 1993). Combined with the local prior knowledge on crop calendars, a simple but reasonable decision tree allowing for a more accurate forest cover classification is built at a regional scale.

4.1.1 Forest cover types in Daxing'anling

Referred to the list of land classes defined by the IGBP (Hansen & Sohlberg, 2000) and the plant functional type map of China (Ran & Li, 2011), which gives the geographical distribution of indigenous vegetation in China, we decided to classify the study area into seven classes to meet with the actual vegetation condition of Daxing'anling area as shown in the following table.

Table 4. 1 Description of land type in the research site combined with the IGBP-DIS definition

Land types	Descriptions
Needle forest	Lands dominated by trees with a percent canopy cover >60% and the dominate tree species is *Larix gmelinii*.
Broadleaf forest	Lands dominated by trees with a percent canopy cover >60% and the dominate tree species is *Betula platyphylla*.
Mixed forest	Forest consists of tree communities with interspersed mixtures or mosaics of other forest cover types.
Shrubs	Lands dominated by bushes and shrubs.
Croplands	Lands covered with temporary crops followed by harvest and a bare soil period.
Residential Place	Land covered by buildings and other man-made structure.
Bare land	Land without vegetation

The needle forest dominated by *Larix gmelinii* is the main forest type in northeast China, especially in Daxing'anling area. It covers the majority of total Daxing'anling. The second type of forest is broadleaf forest dominated by *Betula platyphylla*, which always grew firstly on a fire burned area. Currently, causing by timber harvesting and high frequent forest fires, the forest coverage become fragmented and area with mixed forest tree increased gradually. Cropland here is rare and almost close to settlements.

4.1.2 Method and data processing

In this study, the EVI value derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) data was used as a measure of vegetation intensity on pixel-level, which is a parameter to detect the vegetation change. The vegetation indices composite 16-day global 500 m gird (MOD13A1) was downloaded from the LAADS website (ftp://ladsweb.nascom.nasa.gov/allData/).The tile number covering Daxing'anling area is h25v03. Then, the dataset was converted to the Albers Conical Equal Area projection on datum World Geodetic System 1984 (WGS 84) which is suitable to China (Zhang X, Sun R, Zhang B, & Tong QX, 2008).

In order to remove random noise or eliminate cloud/snow contamination, the harmonic analysis of time series (HANTS) algorithm was employed to transfer the complex raw curve of time-series EVI to a series of sinusoidal waves (Zhou et al., 2015). As shown in Fig 4.1, the abnormal spatial variability can be effectively filtered. Comparing the original curves with the corresponding curves obtained by HANTS analysis, we can see that the EVI data was smoothed after removal of abnormal data and easy to obtain the phenology characteristics of different vegetation.

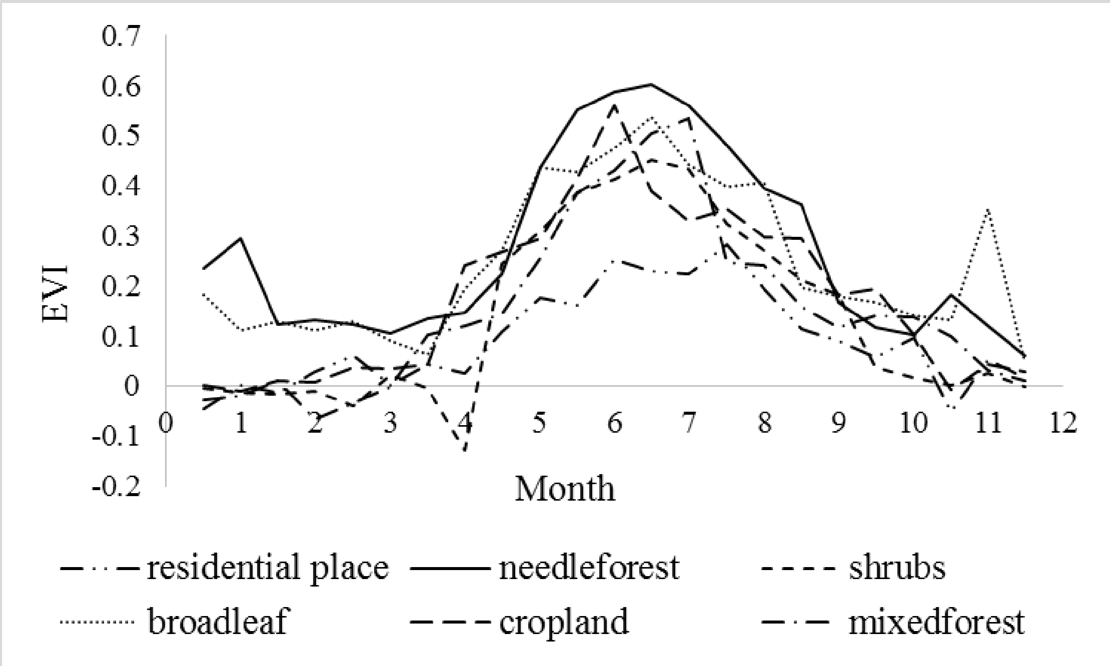
Besides the MODIS EVI products, the 8-day composite MODIS LST data embedded in the MOD11A2 product was used to describe the difference of surface and atmosphere interaction in different land cover classes (Hulley et al., 2014). In order to ensure the uniformity of projection coordinates, the LST dataset also re-projected to the Albers Conical Equal Area projection.

Considering the vegetation distribution is not only determined by a single factor, it is affected by the regional natural conditions (Zhao et al., 2005), such as elevation and slopes. So a digital elevation map (DEM) and a topographical slope map derived from the DEM enabled us to get the regular pattern of vegetation distribution.

4.1.3 Establishment of decision tree

Decision tree theory (Breiman, 1984; Quinlan, 1993) is proposed by Breiman in 1984 and the basic principle is to constitute a binary tree structure through the recursively partitions a dataset into smaller subdivisions (Friedl & Brodley, 1997). This theory has been successfully used in the classification of remotely sensed datasets

(DeFries, Hansen et al., 1998). And as a non-parametric, hierarchical classifier, decision tree classification offers some advantages over other classification methods.



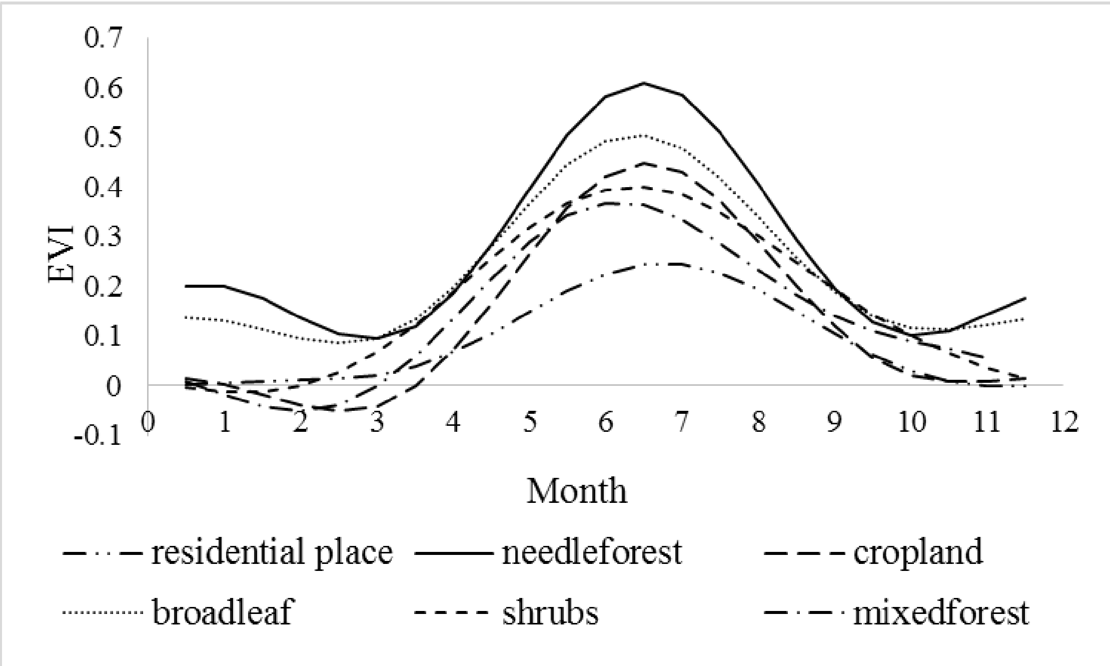


Fig 4. 1The enhanced vegetation index characteristic of different land cover type (up: raw curve, low: processed through HANTs analysis)

The tree is consisted by the root node (from all data), a set of internal nodes and a set of terminal nodes. At each node a splitting rule is applied to discriminate one cluster out from all the data, which resulting in a hierarchical binary tree (Fig 4.2). At the next node the discriminated class is not included so it can reduce the disturbance information from other clusters.

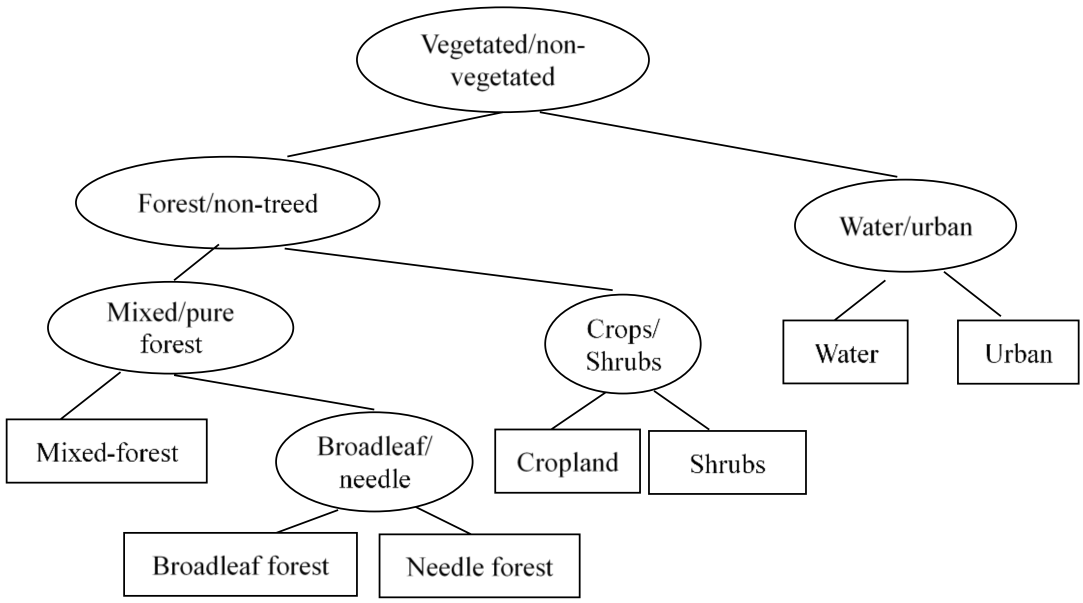


Fig 4. 2 Two-class hierarchical tree classification in forest cover classification

Around Daxing'anling area, since snow falls from October and lasts to March, the growth period of vegetation is very short (from March to September). The land surface is covered by snow so the reflection from vegetation can't be detected by the remote sensor. Taking this special climatic characteristic into account, four vegetation index related variables (Table 4.2) were extracted from the MODIS EVI data to describe the phenological difference between land covers.

Rule-making is critical for decision tree construction. According to the rules, the tree is classified into two branches and the class membership is determine by the class homogeneity. In order to get the spectral heterogeneity and multidimensional clusters, some regions of interest were chosen from Landsat TM as training data because of its high spatial resolution.

All the variables used to constitute a decision tree is listed as below:

Table 4. 2 Metric employed in the decision tree classification

Variable name	Description
EVI-Mar	The mean EVI value in March
EVI-Aug	The mean EVI value in August
EVI-Mean	The average EVI during the vegetation’s growth period
EVI-apl	The amplitude of EVI between August and March
Slope	The slope value derived from DEM
LST	The Land surface temperature
DEM	The elevation value

Combining with the local prior knowledge, the main rules for the tree based on a pixel level are determined as following: first, the residents usually settled down at a flat place so the built-up area is always in flat land and its amplitude of EVI is small and the surface temperature is higher in summer. Second, the shrubs and cropland have higher EVI value in August and lower EVI value in March, and the EVI change of cropland is bigger than the shrubs. Third, the forest has a high average EVI and small EVI change. And the needle forest has a higher EVI in March because the needle forest don’t fall leaves in winter.

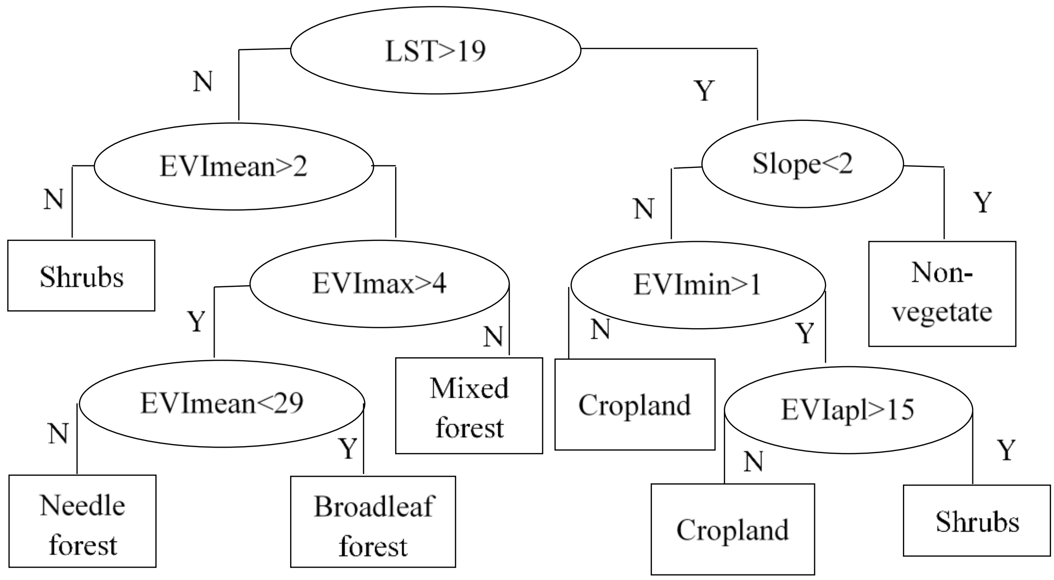


Fig 4. 3 Decision tree classifier in Daxing’anling area

4.1.4 Forest cover classification

The land cover map in 2000 and 2010 were classified using the decision tree classifier developed above. The confusion matrix (Table 4.3) was constructed using ROIs from high resolution images and ground truth data in order to check the accuracy, and it shows the overall accuracy is approximate 75.2%. It can be seen that in some extent, the urban area and cropland were wrongly classified as shrubs because of the coarse resolution. However, our objective is the forest coverage, the accuracy with 75.2% can be seen as effective results in forest cover change analysis at large spatial scales. Finally, the Landsat TM data was used as a base image for artificially correcting the misclassified pixels. The final classification map are shown in Fig 4.4 and Fig 4.5.

Table 4. 3 Accuracy confusion matrix of 2000 MODIS classification

	Cropland	Built-up	Needle forest	Broadleaf	Shrubs	Mixed forest	Barren
Cropland	74.24	4.58	2.89	3.1	3.68	3.02	6.13
Built-up	6.3	78.4	1.61	0.76	1.59	2.17	10.83
Needle forest	2.01	1.88	78.82	6.32	6.32	4.12	3.88
Broadleaf	1.78	1.14	5.61	74.09	8.89	7.46	4.09
Shrubs	10.2	4.35	3.98	5.19	69.65	8.29	8.16
Mixed forest	3.79	1.09	5.29	7.11	8.52	71.11	4.78
Barren	1.68	8.56	1.8	3.43	4.35	3.83	62.13
Total (Percentage)	100	100	100	100	100	100	100
Total (Pixels)	1882	1724	12830	7821	2739	3032	1062

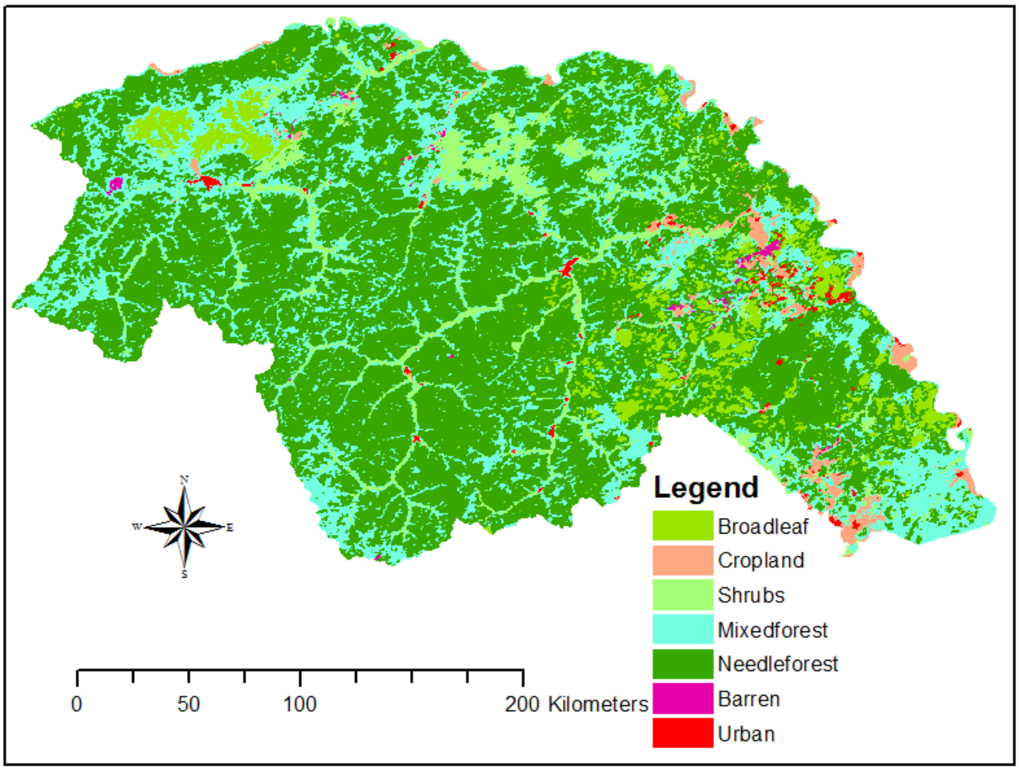


Fig 4. 4 Land cover classification map of Daxing'anling area in 2000

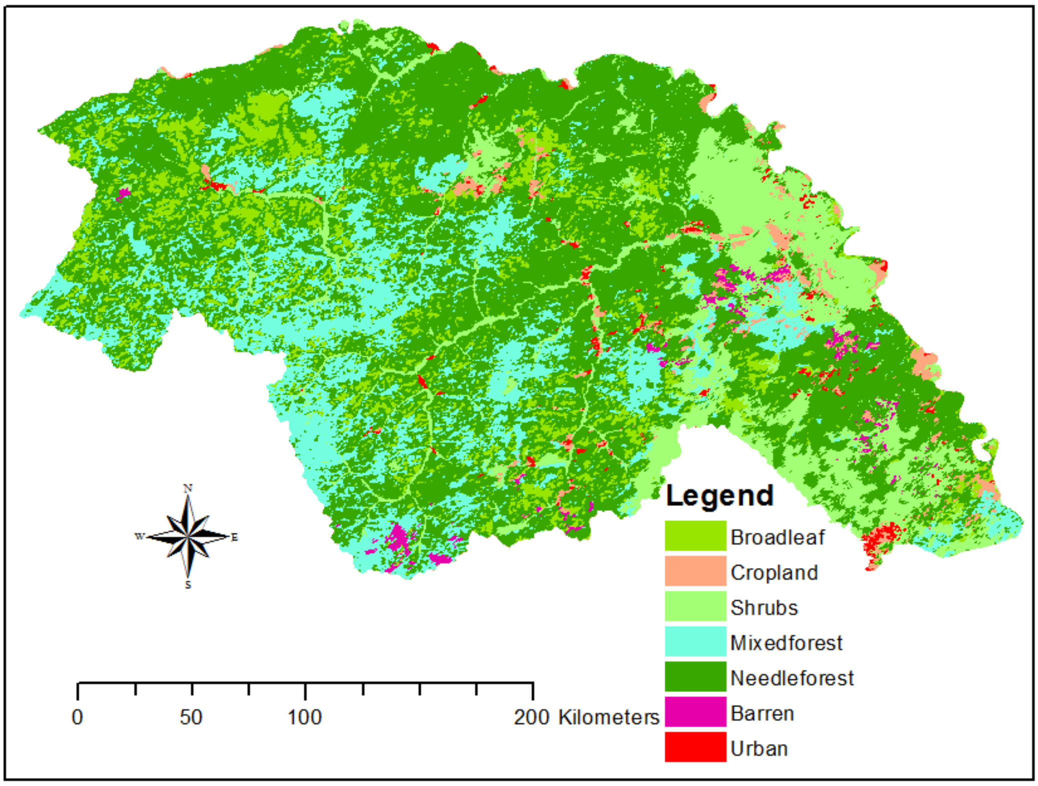


Fig 4. 5 Land cover classification map of Daxing'anling area in 2010

From the figure 4.4 and figure 4.5, we can see that most part of Daxing'anling Mountain is covered by forest, and the forest coverage (needle forest, broadleaf forest and mixed forest) is approximately 88.57% and 80.73% respectively in 2000 and 2010 (Fig 4.6). In the forest stands, the needle forest occupies dominantly and distributes throughout the region. Among the non-forest classes, the shrubs is occupying a large part and mostly distributed near the valley. The residential area is sparsely distributed among the forest but concentrated in the east part of the region.

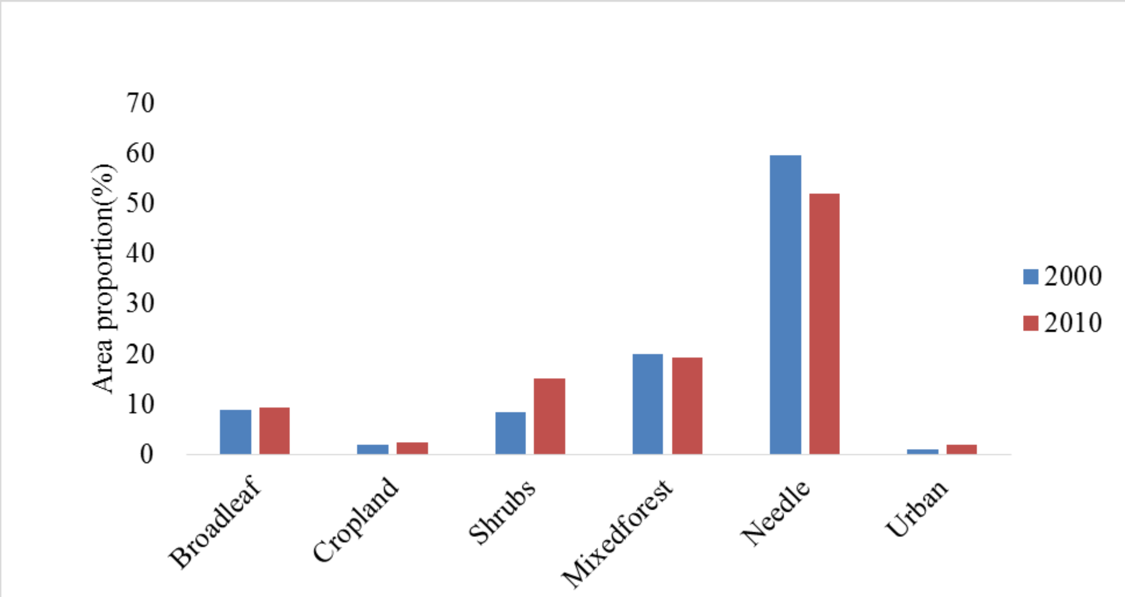


Fig 4. 6 Area proportion of each land type

4.1.5 Detection of forest cover change

Based on the above analysis, it can be seen that the forest coverage in the Daxing'anling Mountain is decreasing from 2000 to 2010, especially the area of needle forest is reducing. Through overlapping of classification map of 2000 and 2010, a map describing the forest change situation can be obtained (Fig 4.7).

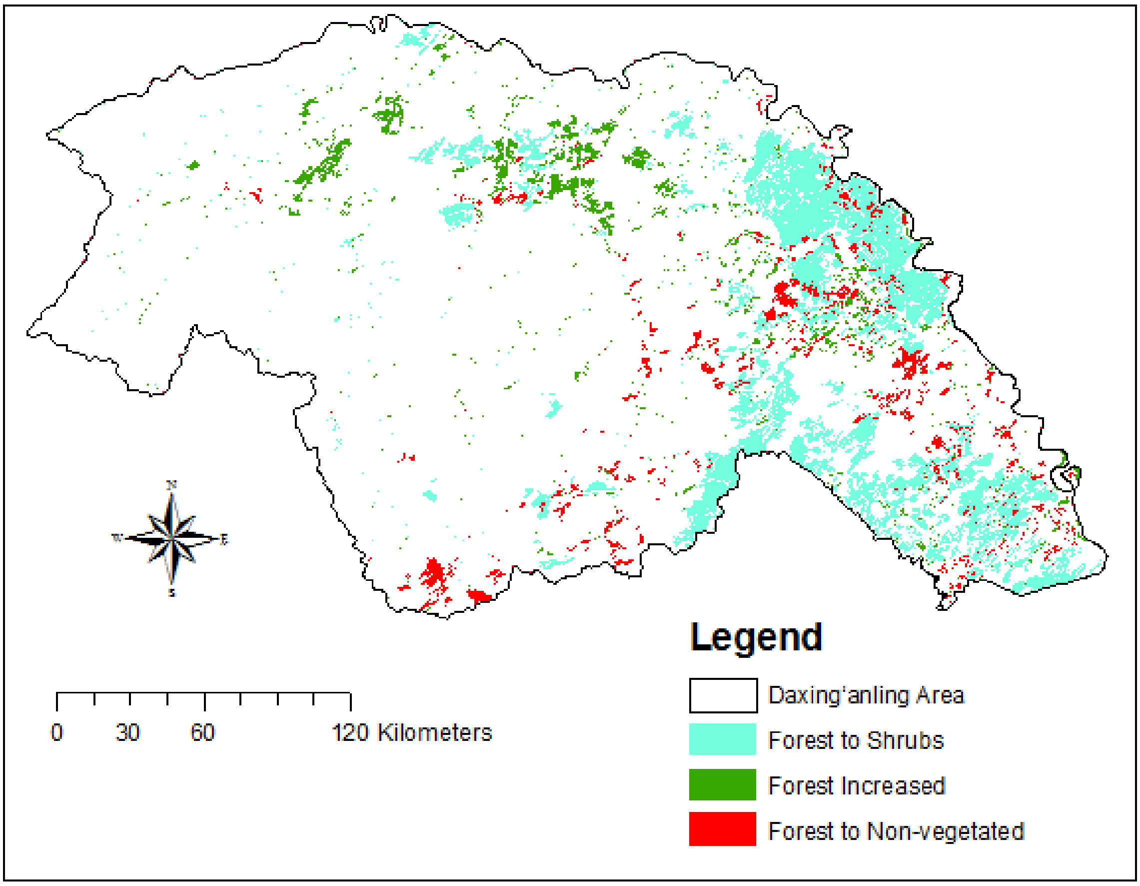


Fig 4. 7 The forest change in Daxing'anling from 2000 to 2010

Here the forest cover change was divided into three kinds: forest converted to non-vegetation land (residence and agricultural area), forest converted to shrubs. And forest increased by means of afforestation. The forest change to non-vegetation mainly happened in the eastern and northern part where the population is concentrated and the demand for residential and agricultural land is relatively high. On the other hand, the forest changed to shrubs in the southeastern and eastern area where, forests are closed to the residence, the people need more fuel wood to keep warm in the long and cold winter, and to take out woods and logs as one major supply of forestry product. Consequently, huge amount of trees were cut down every year.

4.1.6 Discussion and conclusion

The change detection analysis is an efficient way to observe the changes between each land use category. The universal application of the remote sensing technology makes the change detection become possible in a large temporal and spatial scale. Although the spatial resolution of MODIS data is 250m which is not enough for precision researches, by taking the advantage of its high temporal resolution, and combining with other auxiliary data such as Landsat images and DEM map, it is possible to obtain a comprehensive land type information at a large scale. We used the MODIS EVI product, MODIS LST data and DEM data to acquire the variables for establishment of decision tree model. Then an overlap analysis was conducted to detect the forest cover change. The result demonstrate that the majority part of Daxing'anling is occupied by forest, and due to some anthropological activities and natural disturbance, in some area the forest cover transformed to other non-forest cover.

4.2 Extraction of forest fires burnt area

Burned area and occurrence frequency are two indicators used to describe the severity of forest fires. Burned area mapping is particularly important in forest fire research to capture information about the location and timing of fires.

4.2.1 Introduction

Traditional methods of collecting forest fire data are dependent on field surveys which are time consuming and difficult to conduct over large areas (W. Yang et al., 2013). Considering the wide coverage of land surface information, the use of satellite imagery has recently become a popular tool to evaluate the fire damage and contingencies on a global and regional scales (Portillo-Quintero et al. 2013). Until now, various sources of remotely sensed data have been applied to extract areas influenced by fire at a regional (Röder et al. 2008), national (Goetz et al. 2006), and global scale (Chuvieco and Martin 1994; Giglio et al. 2006; Roy et al. 2005). At the regional scale, moderate spatial resolution remote sensing data with high temporal resolution is considered a suitable alternative to extracting a time series burned area map (Emilio Chuvieco, Englefield, Trishchenko, & Luo, 2008). Therefore, Advanced Very High

Resolution Radiometer (AVHRR) (Sukhinin et al., 2004) and Moderate Resolution Imaging Spectroradiometer (MODIS) data (Louis Giglio, Loboda, Roy, Quayle, & Justice, 2009; Roy et al., 2005) have been broadly applied in recent years to map burned areas caused by forest fires. However, because of radiometric instability, cloud obscuration, and sensor transmission problems, AVHRR data were identified as having some potential problems in burned area mapping (Barbosa et al. 1999). The use of MODIS data may reduce these problems and provide better spatial and radiometric resolutions than AVHRR data.

Two methods can be applied to monitor forest fires using remote sensing data according to the different phases of burning: active fire (hotspot) detection (Fraser et al. 2000) and post-fire (scars) burn detection (Bastarrika & Chuvieco, 2011). In hotspot detection, the thermal energy contrast with background pixels and mid-infrared bands is most appropriate for monitoring the active fire. Although burned areas can be evaluated through counting the fire pixel from the active fire detection, the result is somewhat unreliable because of omission errors (L Giglio et al., 2006; Kasischke, 2003). Alternatively, burn scars can be identified by the change of vegetation index and spectral reflectance caused by fires (Carl, 2006; Louis Giglio et al., 2009). However, in some cases, the area of forest clear cuts and harvested croplands are difficult to distinguish from burned areas because of their similar spectral features.

This study proposes an algorithm to discriminate burned areas in the Daxing'anling region, China, using MODIS time series imagery. The algorithm not only considers the thermal abnormalities caused by fires, but also considers the spectral differences in pre- and post-fire vegetation surface. It combines the active fire products that reflect abnormal thermal characteristics with spectral indices that indicate the reflectance difference between pre- and post-fire vegetation surfaces to generate a burned area map on a local scale.

4.2.2 Method and data processing

The primary input data for the burn scar discrimination algorithm included the

MODIS atmospherically corrected level 3 surface reflectance 8-Day composite product (MOD09Q1) time series (Vermote et al. 2002), the MODIS active fire product in a vector format (MCD14DL; https://earthdata.nasa.gov/active-fire-data), and the MODIS enhanced vegetation index (EVI; MOD13Q1).

The algorithm for the MODIS active fire product was based on thermal anomalies that occur during fires (Louis Giglio, Descloitres, Justice, & Kaufman, 2003), and in this research it was applied as a contextual parameter to identify the core pixel of a fire. The surface reflectance composites covered a full year (January 1 – December 31) and only high-quality pixels were processed during analyses. Table 4.4 illustrates the image mask value developed according to the information from the packed quality bits included in the standard MODIS products (http://modis-sr.ltdri.org).

Table 4. 4 MODIS surface reflectance QA science data set bits used to mask low quality data

Surface reflectance state 250 m bit id	0-1	2	3-5	6-7	8-9	10	12	15
Bit description	Cloud state	Cloud shadow	Land/water flag	Aerosol quality	Cirrus detected	Internal cloud mask	Snow/ice flags	Internal snow mask
Value accepted	0	0	1	1-2	0-2	0	0	0

The MODIS data were originally saved in Hierarchy Data Format (HDF) using the sinusoidal projection, and were subsequently re-projected into Albers equal area conic projection which is commonly used in China. The entire study area was then extracted by using the administrative boundary of Daxing'anling.

As the pre- and post-fire spectral differences are the basis of extracting burned areas, it is critical to choose an appropriate spectral index to explain any differences. Recently, the most widely used indices have been the Burned Boreal Forest Index, Burned Area Index (Bastarrika et al., 2014), and Normalized Burn Ratio (NBR) (Hardtke, Blanco, del Valle, Metternicht, & Sione, 2015). Among these indices, NBR was deemed appropriate to extract burned areas in this study because NBR is sensitive to deposits of ash and char caused by forest fires. The Normalized Difference Vegetation Index (NDVI) has also been applied in burned area extraction research because it can offer precise estimations of vegetation condition. However, there are some insufficiencies with the NDVI. For example, the NDVI value may reach its maximum in areas of high vegetation cover (Justice et al., 1998) and cause latent errors for burned area mapping (Barbosa et al., 1999). EVI can overcome the saturation problem in areas with high vegetation coverage such as our study site.

In this study, we used the differenced Normalized Burn Ratio (dNBR) index and EVI to extract the burned areas in Daxing'anling region. Originally, the NBR was developed for use with Landsat images (López & Caselles, 1991) because the near infrared band (B4) is sensitive to living plants and chlorophyll content (Miller & Thode, 2007), whereas the short wave infrared band (B7) provides information about water content in vegetation, lignose in non-photosynthetic vegetation, and hydrous minerals such as clay and ash (Elvidge, 1990).

The NBR value is associated with vegetation moisture content by combining the near- and mid-infrared spectral regions, in which post fire reflectance changes significantly. Unburned sparsely vegetated areas are easily confused with burned areas when using mono-temporal post-fire imagery. Thus, the NBR values obtained pre- and post-fire are generally bi-temporally differenced, resulting in dNBR, which provides a clear contrast between unburned and burned areas.

The formula of NBR index was constructed as:

$$\mathrm{NBR} = \frac{(B4-B7)}{(B4+B7)} \ , \qquad (1)$$

$$\mathrm{dNBR} = (NBR_{pre} - NBR_{post}). \qquad (2)$$

EVI was combined with the dNBR value to reduce potential errors in the process of burned area discrimination.

$$EVI = G \times \frac{(NIR-RED)}{NIR+C1\times RED-C2\times BLUE+L} \qquad (3)$$

where NIR, RED, and BLUE are atmospherically corrected surface reflectances in the near-infrared, red and blue bands. C1 and C2 are the coefficients of the aerosol resistance term and L is the canopy background adjustment parameter. The coefficients adopted in the MODIS algorithm are L = 1, C1 = 6, C2 = 7.5, and G (gain factor) =2.5 (Huete et al., 2002).

Additionally, the MODIS active fire product that can represent thermal characteristics was considered as another contextual restriction to map burned areas.

The proposed algorithm proceeded through two stages as shown in Fig. 4.9. The input data were the NBR data obtained from the MODIS time series images, the MODIS_EVI data, and MODIS active fire data. The algorithm was implemented in two stages and executed iteratively. The first stage attempted to detect the "core pixels", which were deemed as potentially burned by setting threshold values for the input data. The core pixels were then used to discriminate the entire area affected by the forest fire by defining more relaxed criteria for the neighboring pixels around the core pixels.

The first stage was based on the temporal thresholds of EVI and dNBR, combined with the abnormal temperature characteristics. The core pixels fulfilled the following conditions:

1) EVI of the previous period should be above a certain value to ensure that the pre-fire area was vegetated land.

2) The decrease in EVI caused by fires should be persistent and significant, as:

$$(EVI_t - EVI_{t-1})/EVI_t < -0.1. \qquad (4)$$

where t is the 1 month period under consideration. Suppose the *t*-period was the fire period and the t-1 period was the post-fire period. The threshold ensured that the decrease in the post-fire image was sufficient.

3) The dNBR value of the fire period and the following period should be greater than a certain threshold value. The commonly used threshold of the dNBR value was obtained from empirical knowledge, which is likely to vary for different regions. Here, the threshold value was determined from the frequency distribution of dNBR values over a sample year with known fire activity in the area (Fig. 4.8). The histogram of dNBR values displayed a near-Gaussian distribution for unburned areas and an extended tail of positive values for burned areas. In this study, the dNBR threshold of forest fires was initially set at 250, which was defined by the fit of the Gaussian distribution at 95% of the range (Fig. 4.8). However, in the first stage, a relatively high dNBR value was required to detect the forest fire point, therefore, the value was set at 350.

$$NBR_{t-1} - NBR_t > 350. \quad (5)$$

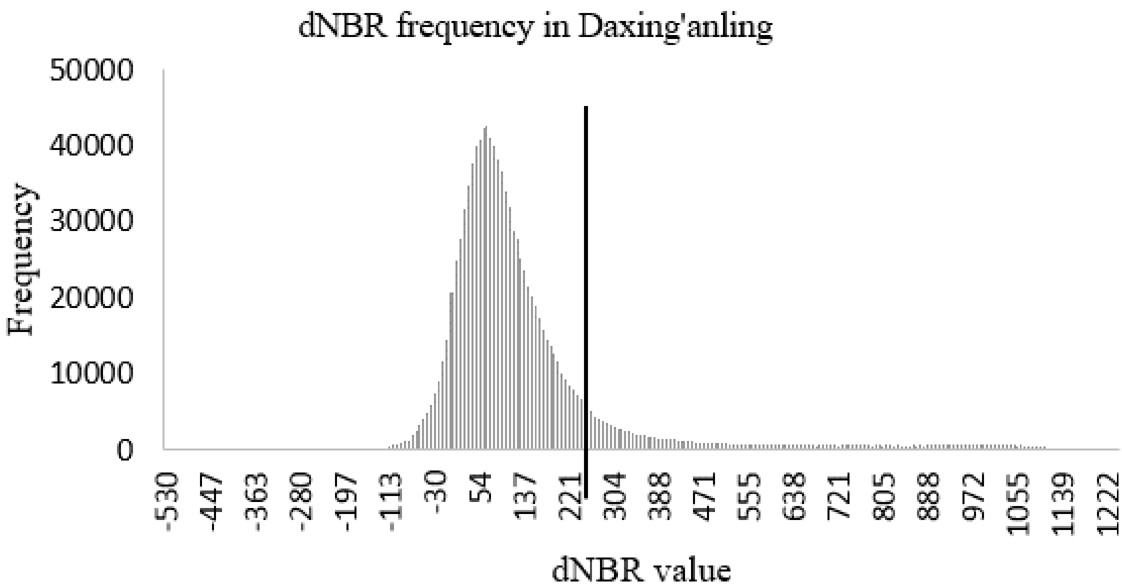


Fig 4. 8 Frequency distribution of dNBR values for threshold determination test windows in Daxing'anling. The solid vertical lines were used to inform the placement of the burn thresholds

After the discrimination of core pixels, more relaxed conditions were applied to detect the area affected by fire from the surrounding pixels. Taking the real conditions of the study site into account, the maximum distance from the core pixels was fixed at 12km and the burned area was discriminated in the 12-km buffer in the second stage as follows:

$$(EVI_t - EVI_{t+1})/EVI_t < -0.1 * 0.5, \qquad (6)$$

$$(EVI_{t+1} - EVI_{t-1})/EVI_{t+1} < -0.1 * 0.5, \qquad (7)$$

$$EVI_{t+2} < EVI_{t-1}, \qquad (8)$$

$$NBR_{t-1} - NBR_t > 250. \qquad (9)$$

Finally, all pixels detected in 1 month were stitched together to form a polygon and a mode filter of 5 × 5 m was applied to remove small polygons. The algorithm was then applied repeatedly for every year from 2001 to 2010. The burned area map was obtained through stacking the resulting polygons together.

4.2.3 Extraction of burned areas

The Daxing'anling region was severely influenced by forest fires from 2001 to 2010, while the extent of the fires differing according to year (Fig.4.10). Among the four administrative districts, Mohe County was the least affected by fires during the study period, with both the smallest total area (85 km^2) and numbers of forest fires. Huma County was the most severely influenced by forest fires with larger fires affecting more areas. The total burned area for Huma County was 5185.5 km^2, which represents approximately 36% of the whole County. During this period, one catastrophic forest fire was detected in 2003. It occurred adjacent to the border between Huma County and Russia, and affected approximately 2,500 km^2 of forest.

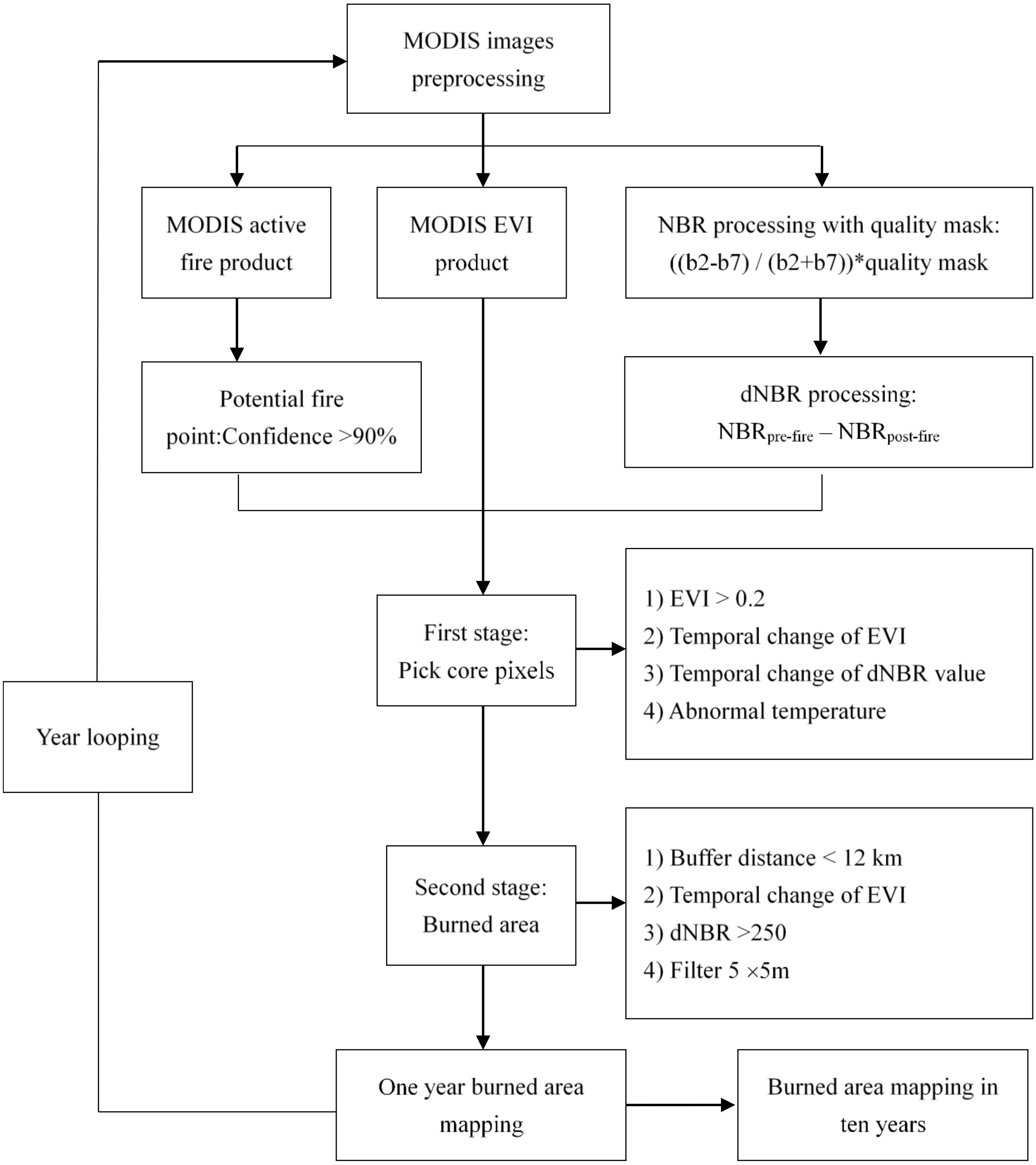


Fig 4. 9 Flowchart of algorithm processing for burned area extraction

The historical fire data for 2000 - 2010 that were obtained from the Bureau of Statistics in Daxing'anling region were used as the validation data to analyze the accuracy of the burned area extractions. The extracted burned areas from MODIS were compared with the fire statistics from the local government. Table 4.5 displays the differentiation between the validation data and the discriminated fire area for each year. The results indicate that the extracted burned areas appear to be only a slight overestimation of actual burned areas in 2001 and 2002. In the other years, the extracted burned areas are smaller than the actual burned areas. A potential explanation for this may be that some low-severity burned areas were ignored because of the high threshold value of dNBR. The results from 2008 were the best estimation of the actual burns with an accuracy of 95.4%; almost all the burned areas were detected. Conversely, the greatest discrepancy occurred in 2003, possibly because of a large fire in that year that spread outside the 12-km buffer distance that may have resulted in some regions of the burned areas being missed. Overall, the discriminated burned areas showed good consistency with the actual burned areas.

Table 4. 5 Validation results for the discriminated burned area using MODIS imagery

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Extracted area (km^2)	42.8	40.8	4136.5	464.3	601.7	598.5	62.8	105.8	77.2	113.6
Actual area (km^2)	31.3	18.7	4461.5	632.3	830.6	730.2	120.4	110.9	90.1	130.3

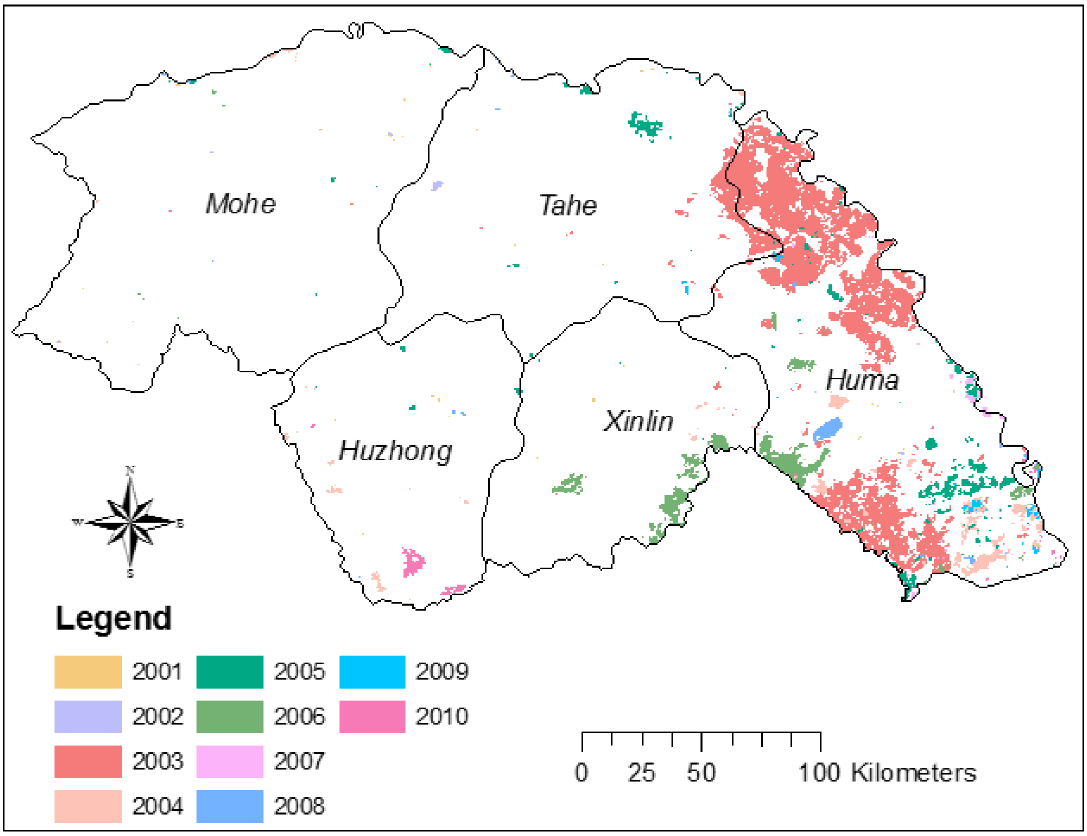


Fig 4. 10 Time series of burned area extraction from 2001 to 2010 in Daxing'anling

4.2.4 Relationship of forests burned area and topographic factors

The study area is a mountainous area that the terrain is complex. In order to find out the relationship between forest fires and topographic factors, we analyzed the correlation among them. As it can be seen from table 4.6, the distribution of burned areas showed a clear negative correlation with elevation, with the burned areas mostly occurring at lower altitudes. Almost 86% of the burned areas occurred below 471m (Table 4.6). A possible explanation may be that the flat area has relatively high temperatures than the mountain area, which may allow fire to spread more easily. Burned areas were also negatively correlated with slope. The burned areas within six slope gradients accounted for almost 90% of the total burned areas during the 10-year period (Table 4.6). There was no significant correlation between burned areas and latitude; however, a clear concentration of burned areas was detected between 50.9°and

52.9° N (Table 3), with more than 90% of burned areas occurring in this range. The upper latitudes (>52.9°N), with relatively low temperatures and low human populations, showed a very low proportion of burned areas (3%).

Table 4. 6 Cross tabulation of burned areas with different auxiliary variables

Factors	Class	Burned area (km^2)	Proportion (%)
Elevation	136 – 340	2816	45.1
(m)	341 – 471	2595	41.6
	472 – 675	417	6.7
	676 – 996	329	5.3
	997 – 1500	86	1.3
Slope	0 – 2.8	4171	66.8
(°)	2.9 – 5.6	1416	22.7
	5.7 – 8.9	383	6.1
	9 – 13.4	204	3.3
	13.5 – 31.3	70	1.1
Latitude	50.91 – 51.9N	2894.3	46.4
(°)	51.91 – 52.9	3148.71	50.4
	52.91 – 53.5	200.99	3.2

4.2.5 Discussion and conclusion

This study presented a burn scar discrimination algorithm and applied it to a time series of MODIS imagery for the Daxing'anling region during a 10-year period from 2001 to 2010. Considering the effects of climate warming caused by fire behavior, the approach focused on a unique combination of vegetation cover, abnormal temperatures and spectral differences between pre- and post-fire surfaces to discriminate burned areas. As a result, commission and omission errors may be reduced using this algorithm, and a more accurate estimation of burned areas may be obtained.

For our proposed algorithm, a critical stage is choosing a suitable threshold value for the spectral indices (EVI and dNBR) between pre- and post-fire surfaces. Different critical values can lead to different accuracy rates. In this study, the frequency distribution of dNBR values was used to determine the threshold, which avoided the subjective influence of previous methods (Loboda et al. 2007). Different dNBR values were then selected during different stages under the threshold value to discriminate burned areas.

Several problems related to the input data may be found when mapping burned areas. For instance, the geographic precision of smaller fire scars was relatively low because of the coarse resolution (250 m) of the MODIS imagery. Another problem is that the quality assessment algorithm applied to the MODIS surface reflectance product can cause an omission of low-quality input data. In addition, atmospheric contamination includes cloud cover in the input data and can also result in large errors during burned area mapping. Although it is possible to reduce these errors using visual checks, it is very time consuming and only suitable for smaller areas.

In this study, inter-annual variability in the spectral index was taken into consideration in burned area extraction, while intra-annual variability in vegetation cover caused by factors such as phenology presented a challenge for single annual threshold implementation in the algorithm. Changing the threshold for the spectral index could improve the accuracy rate in mapping burned areas.

Despite these insufficiencies, the time series of burned areas provides a reliable trend forecast of burned areas in the study region. Through analyzing the burned area maps, the temporal and spatial trends of forest fire occurrence could be identified, for example, the higher impact fires occurred in locations with lower elevations, such as Huma County.

Our proposed algorithm used MODIS time series imagery to extract burned areas, which was the best alternative for regional and long-term burned area mapping. The algorithm not only considers abnormal thermal features, but also takes into account pre- and post-fire spectral differences. Herein, the annual burned areas in Daxing'anling from 2001 to 2010 were mapped using the algorithm. The results showed that the eastern part of study area was frequently affected by forest fire, especially in 2003 and 2005. The burned area mapping approach based on the MODIS time series imagery provides opportunities for further ecosystem-specific refinement. Although the dNBR index may prove useful to differentiate fire impact levels within a single fire scar, proper field validation should be conducted to improve accuracy. Therefore, additional work is necessary for developing dNBR to assess the severity and effects of fires on land surface.

4.3 Detection of forest degradation

In the previous stage, the area of forest cover change and forest fires burned was extracted from remote sensed images. By validating using high spatial resolution images and ground truth data, the accuracy of forest cover change detection and burned area extraction is feasible for this research. According to the statistical data, it is obviously that the forest fires greatly influenced the forest cover change. By overlapping the forest cover classification and burned area map in ArcGIS 10.2, we can understand the spatial relationship of forest degradation and forest fires, as shown in Figure 4.11.

In the environmental risk assessment, it is critical to identify the hazard events. In our research, we attempt to analyze the environmental risk assessment of forest degradation, thus we have to recognize the main cause of forest degradation. From Fig 4.11, it can be seen that, the forest degradation and forest fire burned area has a large area overlapped. Through the statistical analysis, we can know that the intersection part occupied 81.28% of the total forest degradation area, which means that majority of forest degradation area has gone through at least one times of forest fires during 2000 to 2010. Therefore, we can treat forest fires as hazard events caused forest degradation and might have potential influence on other related ecosystem.

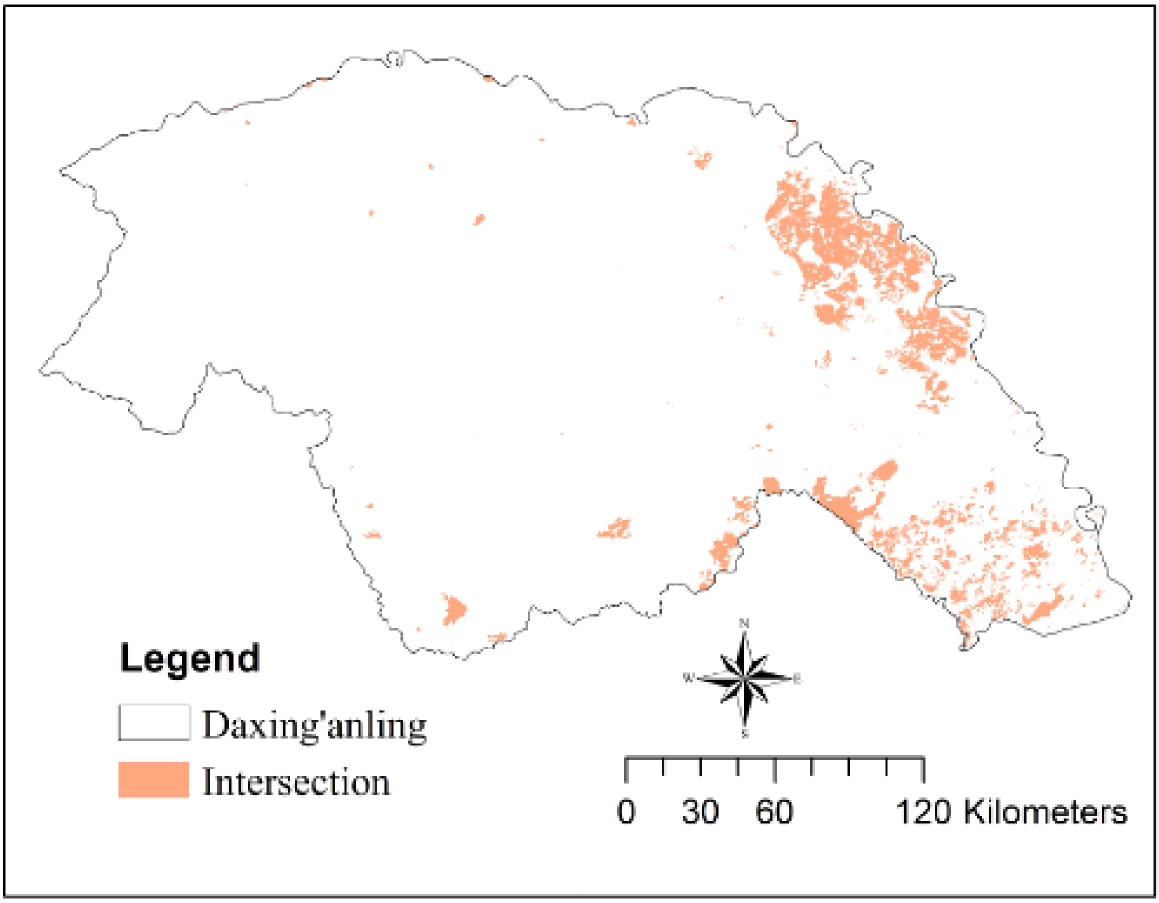


Fig 4. 11 The intersection of forest degradation and forest fire burned area

Chapter 5 Environmental risk assessment

In this chapter, we conduct the process of environmental risk assessment, which is an interaction of hazard events and potential losses. In Chapter 4, we already identified the hazard event caused forest degradation in Daxing'anling area is the occurrence of forest fires. Therefore, in order to get a quantitative analysis of environmental risk, we have to calculate the probability of forest fires and to evaluate the potential losses resulted by forest fires. Thus, in this chapter, a data driven model called weight of evidence (WofE) was employed to map the probability of forest fire occurrence. It is based on Bayesian Theory, which get the posterior probability by using priori probability obtained from historical data, hence it has advantage to avoid the subjective influence on weight allocation. After calculating the probability of forest fires, an evaluation of potential losses is carried out, which is the environmental vulnerability assessment in this research.

5.1 Probability of forest fire occurrence

Natural forest fires play an indispensable role in shaping forest landscapes (Cissel et al. 1999; Seymour et al. 2002; Cleland et al. 2004; Nitschke 2005). According to the Chinese National Bureau of Statistics, more than 10 million hectares of Chinese forest have been affected by forest fires during the past 50 years (Gao 1999). Forest fires can wipe out all vegetation and release large amounts of carbon dioxide (Dokas et al. 2007). Although various forest fire management measures have been implemented to reduce their occurrence, forest fires appear to remain as a major recurrent problem in many regions (Collins et al. 2013). Therefore, monitoring is crucial for fire prevention to decrease the negative effects on the environment and on people (Ballari et al. 2012). Understanding the human and environmental variables that affect forest fires as well as the spatial distribution of such fires is also essential for effective landscape management and fire mitigation. In addition, mapping the probability of a forest fire occurring is necessary to understand the risk of a fire breaking out and the threat posed to humans and ecosystem features such as the atmosphere, the soil, and flora and fauna.

5.1.1 Introduction

In previous studies, considerable attention was paid to describing fire weather conditions and constructing fire indices integrating different meteorological factors. As a result, a wide range of fire risk rating systems and indices were applied to evaluate forest fire risk (Skvarenina et al. 2003; Viegas et al. 1999). Some systems took into account the relationships between moisture, weather conditions, fire fuel properties and fire activity (Wagner 1987). However, Viegas et al. (1999) compared five fire danger indices and demonstrated that they varied significantly because of the different environmental conditions in which they were applied. However, a forest fire is a complicated process influenced both by physical factors and human related factors, and how human activities affect forest fire behaviour is still poorly elucidated.

On the other hands, some studies involved efforts to construct indices that take account of several indicators to predict the probability of forest fires (Chou et al. 1993; Wotton et al. 2003; Preisler et al. 2004; Finney 2005; Syphard et al. 2008; Dlamini 2010; Ganteaume et al. 2012; Eskandari and Chuvieco 2015), different modelling approaches have various strengths and limitations depending on the particular management objectives (Farris et al. 1998). The main difficulty relates to determining the appropriate weight for each indicator in index-based models because of the subjectivity that this inevitably involves (Tiburan et al. 2013). Therefore, an effective approach should be adopted to avoid this problem. As such, in this study, a geostatistical approach that can avoid the influence of subjectivity was applied to estimate the relative rates of contribution of causative factors to forest fires and to build a model for mapping the risk of forest fire occurrence.

The Weight of Evidence method is performed following the equation of the Bayesian probability model (Bonham-Carter et al. 1989), which aims to objectively determine the relative rates of contribution of multiple variables to the occurrence of an event (Engel et al. 1999). It is a data-driven model that unearths the potential linkage between unknown events and causative factors using prior probability and posterior probability derived from historical data (Regmi et al. 2010). In the 1980s, this method was first introduced into the field of geography by a Canadian geologist to identify potential mineral deposits (Agterberg 1989). Since then, it has been demonstrated that the Weight of Evidence method can provide a reliable explanation of evidential factors while avoiding subjectivity (Dong et al. 2011; Lee et al. 2012; Fu et al. 2013). In this study, we attempted to establish a model to broadly characterise the important causative factor layers that may be associated with the occurrence of forest fires. We also used Weight of Evidence model to map the probability of forest fires over a broad spatial scale.

5.1.2 Material and method

5.1.2.1 Spatial data layers

Forest fires are complicated phenomena that affected by a variety of factors including physical and human factors (Chuvieco et al. 2014). Therefore, to completely characterise the behaviour of a potential fire, it is necessary to determine the influential factors acting on forest fires. Based on the previous studies (Chou et al. 1993; Vasilakos et al. 2007; Preisler et al. 2004; Soto 2012; Krawchuk et al. 2008; Pew and Larsen 2001) and considering the availability of data for the area focused on in this study, twelve variables related to fire weather conditions, vegetation composition, topography and human activity were selected to establish a model for mapping forest fire risk.

Meteorological factors including monthly mean temperature (°C), monthly average wind speed ($m \cdot s^{-1}$), monthly mean relative humidity (%) and monthly total precipitation (mm) in fire season (1 March to 31 October) were obtained from China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn). Records of 5 national meteorological stations run by the National Meteorological Administration in northeast China were used to obtain a grid dataset covering the whole study area by kriging interpolation. A digital elevation model (DEM) with 90-m resolution downloaded from the CGIR Consortium for Spatial Information Centre (http://srtm.csi.cgiar.org) was used to extract topographical variables including elevation, slope and aspect using spatial analysis in ArcGIS. Vegetation composition can be seen as the land type cover and the land cover classification at the study site was referring to Zou and Yoshino (2013). Human-related factors including distance from residential areas, population density and road density were chosen to represent the human influence on fires. The data on the total population and the road map in 2009 were obtained from Daxing'anling Statistical Bureau. Then, population density was calculated for each county using equation (1). Road density was calculated for each grid section (1 × 1 km) in the same way, as shown in equation (2). ArcGIS function was used to create a buffer zone for residential areas using a diameter of 2 km.

$$\text{Population density} = \frac{Total\ population\ (pop)}{Area\ of\ county\ (km^2)} \tag{1}$$

$$\text{Road density} = \frac{Length\ of\ road\ (m)}{Gird\ area\ (km^2)} \tag{2}$$

All of the potentially causative factors were processed in ArcGIS and georeferenced to Albers equal area conic projection based on the World Geodetic System 1984 (WGS 84), which is commonly used in China. Because the analytical approach of the Weight of Evidence method required categorical rather than continuous input data, all input maps were categorised into different classes with equal intervals. They were then converted to a 1×1 km grid in ArcGIS grid format, which can be directly inputted into the Weight of Evidence model.

The forest fire season in Daxing'anling prefecture is from 1March to 31 October, during which forest fires are prone to occur due to dry weather condition (Tian et al. 2013). A digital database of the occurrence of forest fires during the fire season in 2009 was compiled based on the MODIS active fire product (MOD/MYD 14) in Daxing'anling Prefecture with a spatial resolution of 1 km (Giglio et al. 2004). This product provide information about time, location of burning (limited to a 1 km pixel) and the confidence of detection estimate. The burnings with confidence level larger than 90% were used as training data in the model.

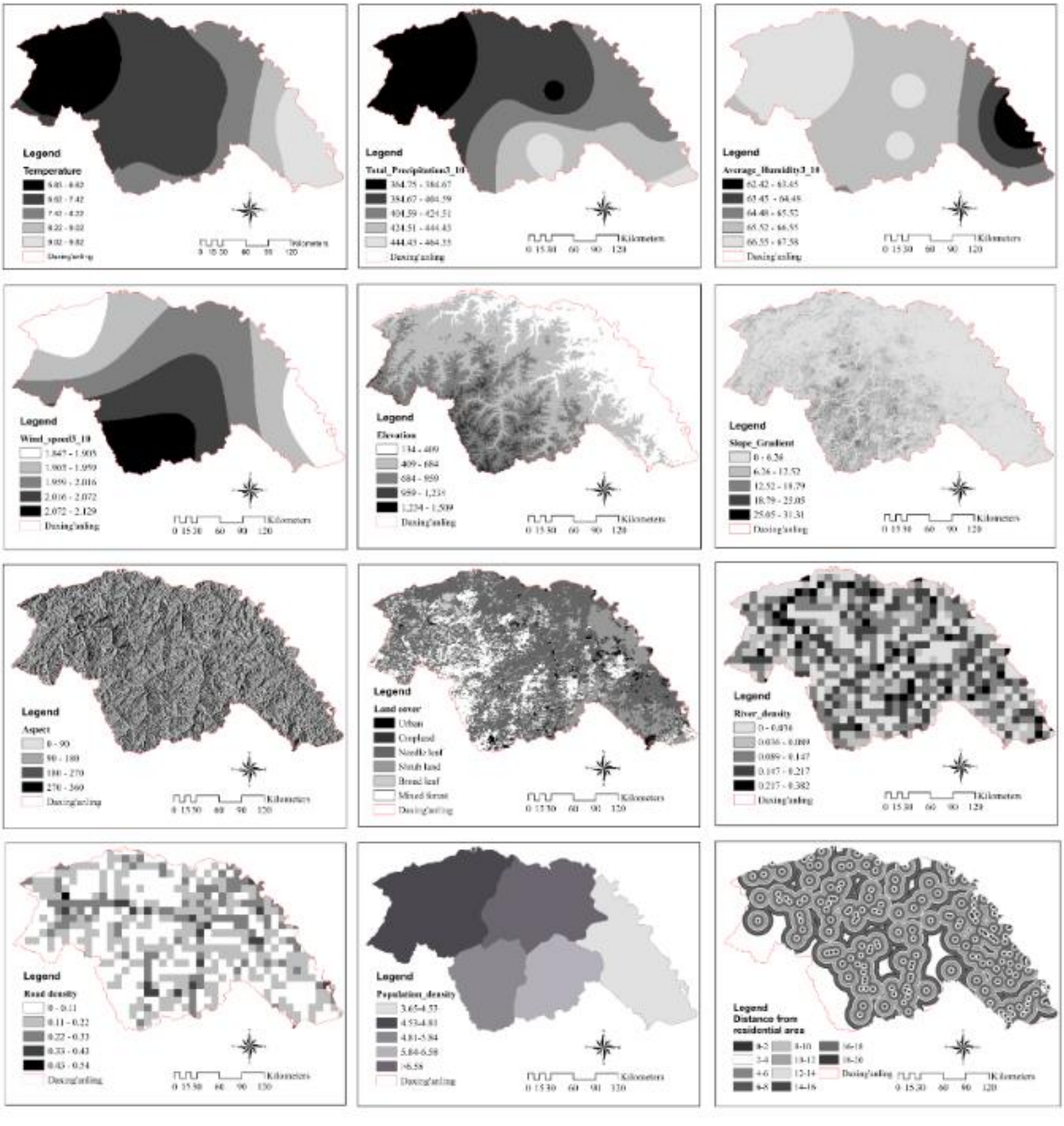


Fig 5. 1 Spatial data input in weight of evidence analysis

5.1.2.2 Weight of evidence model

A Bayesian probability method, named weights of evidence (WOE) model (Bonham-Carter et al. 1989) was employed to quantify the risk of forest fires. It requires a spatially defined study area, a set of training points (known occurrences of forest fires), and a set of spatial data layers (input maps) as evidence layers. WOE model can provide a measure of spatial association between training points and evidence layers (Romero-Calcerrada et al. 2008), and the evidence layers are assumed to be conditionally independent with respect to the training points (Agterberg et al. 1993).

Take a study site T, with a total area A (T). Then it is divided into unit cells with equal size u km2; thus the number of cells on study area is N (T) = A (T)/u. The number of cells with a fire occurred is N (D), so prior probability P (D) was computed as P (D) = N (D)/N (T). The prior probability is a non-conditional probability and is a constant throughout the whole study. Odds ratio (O) of prior probability that a randomly selected cell include a fire occurrence was computed by the prior probability as

$$O\ (D) = \frac{P(D)}{P(\bar{D})} = \frac{P(D)}{1 - P(D)} \qquad (3)$$

Where $P(\bar{D})$ is the prior probability that a fire event didn't occur in that cell.

For a given set of evidence layer E_i, where i = *1, 2, 3, …, n*, and *n* is the total number of evidence layer, where each of them represents an independent causative factor. Thus the conditional posterior *P (Ei/D)* was expressed as odds:

$$O(E_i|D) = O(D)\frac{P(D|E_i)}{P(\bar{D}|E_i)} \qquad (4)$$

According to Bayes' rule, and the fundamental assumption that the input evidence layers are conditional independent, the following equation can be derived

$$O(E_i|D) = \ O(D)\frac{P(E_i|D)}{P(E_i|\bar{D})} \qquad (5)$$

And then take the natural logarithms on both sides of the equation:

$$\ln\big(O(D|E)\big) = \ln\left(O(D) \times \frac{P(D|E_1 \cap E_2 \cap E_3 \cdots E_n)}{P(\bar{D}|E_1 \cap E_2 \cap E_3 \cdots E_n)}\right)$$

$$= \ln\left(O(D) \times \frac{P(E_1 \cap E_2 \cap E_3 \cdots E_n|D)}{P(E_1 \cap E_2 \cap E_3 \cdots E_n|\bar{D})}\right)$$

$$= \ln\big(O(D)\big) + \ln\left(\frac{P(E_1|D)P(E_2|D)P(E_3|D) \cdots P(E_n|D)}{P(E_1|\bar{D})P(E_2|\bar{D})P(E_3|\bar{D}) \cdots P(E_n|\bar{D})}\right)$$

$$= \ln\big(O(D)\big) + \mathrm{In}\left(\frac{P(E_1|D)}{P(E_1|\bar{D})}\right) + \ln\left(\frac{P(E_2|D)}{P(E_2|\bar{D})}\right) + \cdots$$

$$+ \ln\left(\frac{P(E_n|D)}{P(E_n|\bar{D})}\right) \qquad (6)$$

In WOE model, two kinds of weight (W^+ and W^-) for evidence pattern i of each evidence variable is defined as below:

$$W_i^{\,+} = \ln\frac{P(E_i|D)}{P(E_i|\bar{D})} \qquad (7)$$

$$W_i^{\,-} = \ln\frac{P(\bar{E}_i|D)}{P(\bar{E}_i|\bar{D})} \qquad (8)$$

Thus, the log odds of posterior probability might be calculated through adding W^+ or W^- for presence or absence of each evidence layer to log odds of the prior probability as below

$$\ln\big(O(D|E)\big) = \ln\big(O(D)\big) + W_1^+(OR\ W_1^-) + W_2^+(OR\ W_2^-) + \cdots W_n^+(OR\ W_n^-)$$

$$= \ln\big(O(D)\big) + \sum_{i=1}^{n} W_i^k \qquad (9)$$

where

$$W_i^k = \begin{cases} W_i^+\ , & if\ the\ evidential\ layer\ i\ is\ present; \\ W_i^-\ , & if\ the\ evidential\ layer\ i\ is\ absent; \\ 0\ , & original\ data\ loss; \end{cases}$$

Then the posterior probability of unit cell $P(D|E_i)$ calculated from the logit equation

$$P(D|E_i) = \frac{O(D|E_i)}{1 + O(D|E_i)} \quad (10)$$

$$\mathrm{C} = W^{+} - W^{-} \quad (11)$$

where W^{+} and W^{-} are the weights in the presence and absence of the causative factor, respectively. P is the conditional probability, B and $\bar{B}$ is the area where predictive pattern is present and absent respectively, D and $\bar{D}$ in terms of the area where forest fire occurrence is present and absent. The magnitude of W^{+} shows a positive relationship between the presence of the causative factor and forest fires; similarly, the magnitude of W^{-} indicates the level of a negative relationship (Regmi et al. 2010). In general, absolute weight values between 0 and 0.5 show a mildly predictive capacity, values between 1 and 2 are strongly predictive and those greater than 2 are extremely predictive (Agterberg et al. 1993; Neuhäuser and Terhorst 2007; Ozdemir 2015).

C is the difference in these two weights, being called the weight contrast, which indicates the spatial association among the causative factors and forest fires (Dahal et al. 2008). A larger weight contrast implies stronger spatial association between causative factor and forest fires (Romero-Calcerrada et al. 2008). If C is zero, this means that the causative factor has a negligible influence on forest fires. A positive C implies a positive spatial correlation and negative C suggests a negative one (Corsini et al. 2009). However, in some case the contrast value might become meaningless due to less number of training point (Oh and Lee 2010). The studentized value of C (Cs) can serve as a useful measure of the significance of the spatial association (Agterberg et al. 1993)and act as a cut off to categorize causative factors into binary patterns as favourable and unfavourable layer (Dilts et al. 2009).

The Arc-SDM (Kemp et al. 2001) spatial data modeller extension to ArcView 3.3 was used to conduct the Weight of Evidence analysis, which enabled the probability of a fire per 2 km^2 area throughout the whole of the study area to be reported.

5.1.2.3 Test for pair-wise conditional independence

The Weight of Evidence model involves the fundamental assumption that the causative factors are conditionally independent of each other. Therefore, tests of conditional independence were conducted before the integration of the evidential factors to generate the posterior probability map of forest fires. A chi-square test was adopted to investigate the significance of differences between two factors. The chi-square table for testing conditional independence between all pairs of factors is shown in table 5.1. The χ^2 value of 6.63 was calculated at the 99% significance level with 1 degree of freedom.

Table 5. 1Pair wise Chi-square statistic of 12 factors

Factors	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	1.10	0.47	0.06	0.36	0.21	1.69	0.01	0.00	4.23	0.26	0.38
(2)		5.09	0.74	0.06	18.54	11.35	6.45	62.96	12.07	11.11	108.69
(3)			21.38	20.35	64.13	1.69	1.26	39.01	2.33	1.54	2.76
(4)				57.17	1.61	0.03	0.39	13.92	0.51	4.15	2.07
(5)					5.49	0.56	3.06	6.19	2.93	3.00	0.75
(6)						0.01	3.17	42.98	2.20	3.16	4.62
(7)							1.65	11.94	0.01	5.16	20.00
(8)								13.64	5.58	3.83	49.17
(9)									1.12	10.56	186.46
(10)										0.00	3.33
(11)											2.31

(1). Aspect; (2). Elevation; (3). Precipitation; (4). River density; (5). Road density; (6). Wind speed; (7). Slope gradient; (8). Humidity; (9). Temperature; (10). Distance from residential area; (11). Land cover; (12). Population density

If the χ^2 value between two factors in table 2 is below 6.63, the pair of these two factor is conditional independent. As an example, the chi square between aspect and elevation is 1.10 (Table 1) is smaller than 6.63, which implies they are conditional independent and could be used together to map the risk of forest fires. However, the pairs of elevation and temperature show conditional dependence, because the chi-square is 62.96 above 6.63. This means that these two factor could not be employed together in mapping forest fire risk.

By checking the chi-square statistic table, the high χ^2 value between elevation and wind speed, slope gradient, temperature, distance from residential area and population density indicate elevation is conditional dependent with wind speed, slope gradient, temperature, distance from residential area and population density (Table 5.1). Likewise, precipitation is dependent with river density, road density, wind speed and temperature; temperature is conditional dependent with elevation, precipitation, river density, wind speed, slope gradient and humidity. Finally, a combination of conditional independent factors including aspect, distance from residential, slope, river density, road density, wind speed, population density and land cover type was applied in WOE model.

5.1.3 Results of weights for evidential layers

In the Weight of Evidence model, the causative factors selected from conditional independent test were treated as input data, while the sites at which forest fires had occurred in 2009 were adopted as training points. The number of training points was approximately 271, and the unit cell for the Weight of Evidence model was set at 2 km. By using Bayesian probability analysis (equation (7, 8, 11), the positive weight (W^+), negative weight (W^-) and C can be calculated (Table 5.2).

As mentioned before, the magnitude of W^+ and W^- represent the predictive capacity of the causative factor to forest fires, therefore the aspect and road density factor were removed from the WOE model because the magnitude value of W^+ and W^- are lower than 0.5. The final model for forest fires occurrence in Daxing'anling prefecture included 6 evidential factors as slope gradient, river density, wind speed, land cover type, population density and distance from residential area. After that, in order to generate a dichotomous pattern for each causative factor, we reclassified the factors into favourable and unfavourable layers based on the value of studentized C. Here take the variable distance from residential areas as an example. We can see that

Table 5. 2 Weight of Evidence analysis for forest fires and related causative factors

Factors	Class	W^{+}	W^{-}	C	S(C)	STU(C)
Slope gradient	0–6.26	0.48	-0.81	1.29	0.23	**5.56**
(°)	6.26–12.52	-1.22	0.15	-1.37	0.27	-5.15
	12.52–18.79	-0.64	0.02	-0.66	0.45	-1.45
	18.79–25.05	NaN	NaN	NaN	NaN	NaN
	25.05–31.31	NaN	NaN	NaN	NaN	NaN
Aspect	0–90	0.06	-0.03	0.09	0.13	0.68
(°)	90–180	-0.07	0.02	-0.09	0.14	-0.61
	180–270	0.08	-0.02	0.10	0.14	0.7
	270–360	-0.09	0.03	-0.11	0.15	-0.76
River density	0–0.036	0.69	-0.07	0.76	0.32	**2.38**
(km/km^2)	0.036–0.089	-0.24	0.13	-0.37	0.13	-2.85
	0.089–0.147	0.23	-0.05	0.28	0.15	1.85
	0.147–0.217	0.07	-0.002	0.07	0.32	0.21
	0.217–0.382	0.24	-0.003	0.27	0.34	0.79
Average wind	1.847–1.903	0.7	-0.23	0.93	0.13	**7.15**
speed	1.903–1.959	0.48	-0.21	0.69	0.13	5.47
(m/s)	1.959–2.016	-0.69	0.18	-0.87	0.17	-5
	2.016–2.072	-0.76	0.12	-0.88	0.21	-4.11
	2.072–2.129	-0.89	0.08	-0.97	0.28	-3.39
Land use	Urban	1.72	-0.08	1.79	0.22	8.22
	Cropland	0.55	-0.02	0.57	0.33	1.74
	Needle leaf	-0.93	0.57	-1.49	0.15	-10.19
	Shrubland	1.2	-0.5	1.7	0.12	**13.87**
	Broadleaf	-0.52	0.04	-0.56	0.28	-2.04
	Mixed forest	-0.35	0.06	-0.41	0.17	-2.19
Population	365–453	1.18	-0.99	2.18	0.13	**16.19**
density	453–481	-1.57	0.27	-1.85	0.26	-7.17
(10^{-2} pop/km^2)	481–584	-0.37	0.05	-0.42	0.21	-2.01
	584–658	-1.67	0.12	-1.79	0.38	-4.66
	>658	-0.73	0.14	-0.87	0.19	-4.39
Road density	0–0.11	0.02	-0.02	0.04	0.12	0.30

(km/km^2)	0.11–0.22	0.06	-0.04	0.1	0.12	0.81
	0.22–0.33	-0.15	0.02	-0.17	0.17	-0.91
	0.33–0.43	-0.26	0.01	-0.27	0.50	-0.54
	0.43–0.54	NaN	NaN	NaN	NaN	NaN
Distance from	0–2	0.93	-0.06	0.99	0.22	**4.58**
residential	2–4	0.61	-0.1	0.72	0.16	4.39
areas (km)	4–6	-0.03	0.00	-0.03	0.19	-0.16
	6–8	0.16	-0.03	0.19	0.17	1.12
	8–10	-0.43	0.06	-0.49	0.22	-2.22
	10–12	-0.33	0.04	-0.37	0.22	-1.68
	12–14	-0.27	0.03	-0.3	0.23	-1.33
	14–16	-0.33	0.03	-0.36	0.26	-1.39
	14–18	-0.29	0.02	-0.31	0.29	-1.06
	18–20	-0.33	0.01	-0.34	0.36	-0.95
	20–	NaN	NaN	NaN	NaN	NaN

(W^+ and W^- values in bold indicate the weights of the dichotomous predictor pattern of each factor.)

studentized C has the highest value of 4.58 in the range below 2 km; therefore, the layer below 2 km was classified as a favourable layer and that above 2 km was set as an unfavourable one. Then, the positive weight and negative weight were applied as rating values for the range below 2 km and other ranges. By analysing the other factors in a similar way, we were able to obtain a dichotomous pattern for each causative factor.

5.1.4 Probability of forest fire occurrence

The prior probability was 0.0042, calculated as the total forest fire events over the area of study region. And all of the dichotomous patterns for each conditional independent variable were inputted into the Weight of Evidence model to generate the posterior probability map of forest fire occurrence. From a visual interpretation of the risk of forest fires (see Fig. 5.2), it was considered that the probability map of the occurrence of forest fires should be divided into different levels. In this study, we divided the posterior probability into four levels: potential, low, medium and high by employing the natural breaks classification (Apan 1997), which can objectively and rationally explore the statistical distribution of classes in an attribute space.

For Daxing'anling prefecture we analysed, the maximum posterior probability of forest fire occurrence was not so large, only approximate 0.224. It can be seen that the zones with high susceptibility to forest fires are generally located in the east of Daxing'anling. The combined effects of meteorological conditions, topography and human activities make this region particularly vulnerable to forest fires, with a large part of it being classified as a high susceptibility zone for forest fires. The zones with a relatively high probability (posterior probability > 0.023) of forest fires occupy approximately 4% of the total area. Zones with lower risk (posterior probability < 0.003) occupy approximately 91% of the total area and are generally located in the western part of Daxing'anling.

A studentized uncertainty statistic for each cell was applied to evaluate the uncertainties associated with the posterior probability map. It calculated as

$$\sigma(stu) = \frac{P_{psot}}{\sigma_{TOTAL}} \tag{12}$$

in where, the total uncertainty was the variance in the weights (Bonham-Carter et al., 1989), and it comprised by uncertainties due to missing data or incomplete values in overlapping input data.

$$\sigma^2\ (TOTAL) = \sigma^2\ (WEIGHT) + \sum_{i=1}^{n} \sigma^2\ (MISSING) \tag{13}$$

If the value of studentized uncertainty smaller than 1.96, it means the cells is with significant uncertainty (α=0.05) (Bonham-Carter et al. 1989). As can be seen from Fig 5.2 (low), the overall studentized uncertainty if greater than 2, which indicate the uncertainty level for posterior probability map can be accepted.

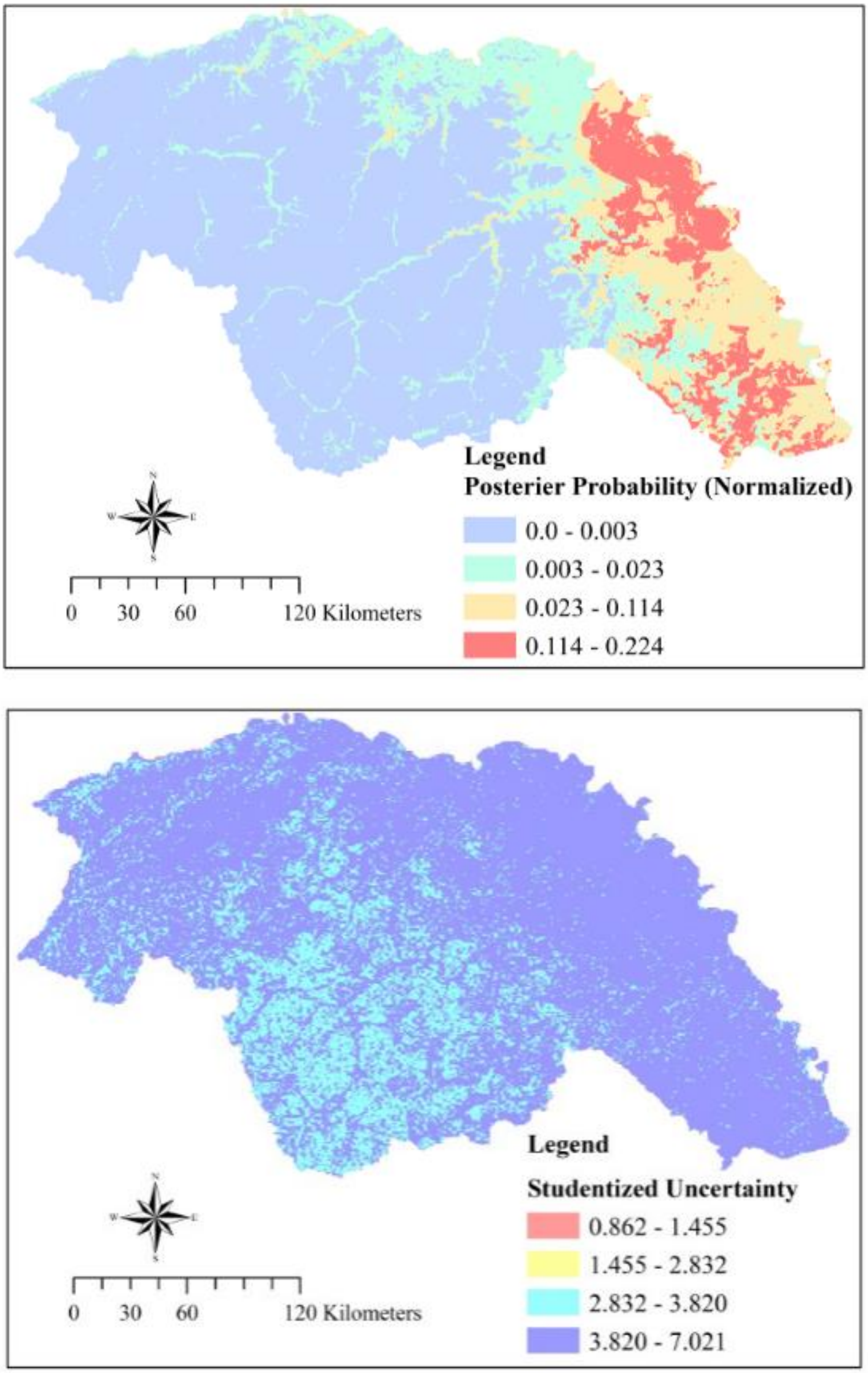


Fig 5. 2 Normalized posterior probability of forest fire occurrence (up) and studentized uncertainty values (low) for all forest fires (n=271) among the study area. Ranges for all values are scaled using a natural breaks classification.

In this research, the ROC curve (Swets et al. 2000)was used for model validation, which was performed through comparison with existing forest fire events data (Fig 5.3). It compares the probability value derived from WOE model with the actual forest fire events. The area under the ROC curve (AUC) was commonly used to define the quality of a prediction model by describing the performance to identify the occurrence or non-occurrence of forest fires (Yesilnacar and Topal 2005). From fig 5.3, we can understand that probability above 10% could explain 85% (AUC=0.85) of the forest fire occurrence, which show a relatively high accuracy for the WOE model.

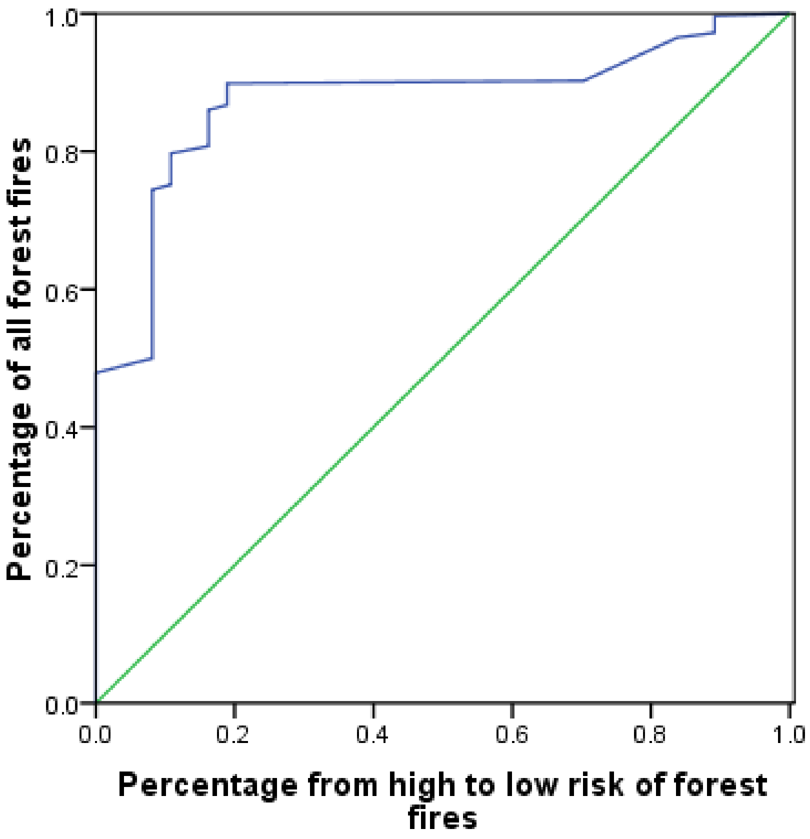


Fig 5. 3 ROC curve evaluation for weight of evidence analysis

5.1.5 Discussion and conclusion

5.1.5.1 Discussion

Forest fires show an irregular spatial distribution in Daxing'anling Prefecture, which our research suggests is influenced by both physical and human factors. Thus, a data mining statistical model was considered to be suitable for modelling the occurrence of fires there. Results showed that this model was relatively good at predicting fires. Although previous studies suggested that forest fires are strongly related to weather conditions (Viegas et al. 1999; Skvarenina et al. 2003; Wotton et al. 2003), due to conditional dependence, only average weed speed was adopted in WOE model. As shown in Table 5.2, the high studentized contrast value appears in the range between 1.84 and 1.9 m/s, thus this average wind speed range can be seen as a promoter of forest fires.

In our WOE analysis, through conditional independent test, we select three topographical factors for mapping forest fires, however, aspect factor was not a highly ranked predictor for forest fire occurrence in Daxing'anling prefecture. As for the factor of slope gradient, its predictive capacity for forest fires is not so strong since the highest W^+ is 0.48, which is smaller than 0.5, however, the studentized contrast value reached to approximate 5.6, which means the spatial association between slope gradient and forest fire occurrence is significant. We identified the favourable range of slope is below 6.26 °, which indicates that forest fires are more likely to start in areas with a gentle slope. River as a barrier to slow down fire spread also play an important role in mapping forest fire occurrence. In our analysis, the lower river density between 0-0.036 km/km^2 was set as a favourable layer which means the less the number of rivers, the easier the forest fires occur. Similar analysis also employed for factors related with human activities, population density, road density and distance from residential areas are variables that influence forest fires, and forest fires generally occur at sites with intensive human activities. Therefore, in Daxing'anling Prefecture, the impact of human activity on forest fires in recent years cannot be overlooked.

By overlaying the weighted influential variables in ArcGIS 10.2, a posterior probability of forest fires was calculated, which ranged from 0 to 0.224. The higher the probability, the greater the susceptibility to forest fires. Overall, the zones vulnerable to forest fires occupy approximately 10% of the total study area and are almost all located in the eastern part of this area. This might be a consequence of the combined effects of weather conditions, topography, fuel features and human activities. Although the low-risk zones occupied a large proportion of the total area, mitigation measures should also be considered in these zones to avoid potential damage caused by forest fires.

GIS technologies provide a means of integrating multi-source information and data into decision-making processes, through which a quantitative assessment over a broad range of spatial and temporal scales can be carried out. In addition, in this study, the assignment of weight to each variable that potentially influences forest fires was successfully improved using a Bayesian framework by specifying the prior probability, which avoided subjectivity and resulted in a relatively objective weight assignment.

5.1.5.2 Conclusion

This study focused on the influences of a range of variables on the occurrence of forest fires, using a Weight of Evidence model to characterise the spatial distribution of forest fires in Daxing’anling Prefecture, China. Twelve variables related to climate conditions, topographical features, fire fuel characteristics and human activities were selected based on previous studies on the effects of such variables and the availability of data for the study area. Our results indicate that forest fires occurred nonrandomly, being significantly related to environmental variables. The results suggest that six variables, namely, average wind speed, slope gradient, river density, land cover type, population density and distance to residential areas, have relatively strong influences on forest fires. Via the Weight of Evidence analysis, the active layer of each variable was identified. For example, for the variables of slope gradient, a gentler slope (0–6.26°) were found to be associated with a higher probability of forest fires.

This research also indicates that the probability of forest fires in Daxing’anling differs across the region, in that the eastern part has a relatively high probability of forest fires, and thus might warrant extra measures to manage the threats to the environment and humans there. In contrast, the western part has a low occurrence of forest fires. These results provide a rational basis on which forest managers can make decisions to mitigate damage due to fires.

5.2 Environmental vulnerability assessment

Within the study area, extremely low winter temperatures help to develop an underground permafrost soil layer that can be envisioned as the southern edge of the Eurasian permafrost zone (Jin et al., 2007). The permafrost soil zone has strong effects on biogeochemical processes such as oxidation/reduction and decomposition (Ping et al., 2015). Moreover, the large amount of organic carbon that has accumulated in these soil layers make them prominent in global climate research (Bobrik et al., 2014) because thawing of this permafrost is predicted to release large amounts of greenhouse gas. However, the permafrost in the region is sensitive to climatic warming, which makes the forest ecosystem susceptible to climate change. The change of the permafrost soil layer can be seen as a sign of global climate change and once this permafrost is destroyed, recovery to its original state is considered difficult in the coming decades and centuries (Wang, 2005). Therefore, Identifying ecologically vulnerable regions is an important aspect of forest resource management, especially in boreal forest ecosystems that exhibit sensitivity to climate change. In this study, the environmental vulnerability was understood as the potential losses of the environmental system when exposed to the forest degradation. It is the important step in environmental risk assessment.

5.2.1 Introduction

Forest ecosystems are under increased stress that has been linked to climate change (Mildrexler et al., 2015) resulting in the common problem of forest degradation in China (Xiao et al., 2004). The forest ecosystem of the Daxing'anling region in northeast China represents the southern-most part of the global boreal forest biome (Jiang et al., 2002), one of the most ecologically fragile and economically under-developed region in China (Huang et al., 2010). This region is particularly sensitive to changes in temperature and other environmental conditions (Luo and Xue, 1995). The ecosystem here plays important roles in biodiversity conservation and climate mitigation. However, it is affected by various types of natural and anthropogenic disturbance. In recent years, economic development and timber harvest operations have exacerbated the imbalance between environmental protection and economic development (Hong et al., 2002), which creates several problems related to the management of forest resources. Identifying vulnerable areas plays an important role in forest resource management, especially in fragile regions such as the Daxing'anling. To help decision makers formulate effective forest management strategies, conducting a comprehensive environmental vulnerability evaluation is imperative. This type of evaluation enables the identification of areas at risk of losing functions that will threaten future efforts related to sustainable land management. However, scientists have found vulnerability difficult to quantify because the qualitative nature of vulnerability indicators makes it difficult to develop precise and objective measurements of vulnerability.

The term of "environmental vulnerability" is related to the risk of damage to the natural environment or a particular ecosystem type. According to the Intergovernmental Panel on Climate Change (IPCC 2014), vulnerability is the degree to which a system is susceptible to adverse effects caused by a specific hazard or stressor. Understanding the factors that affect vulnerability is critical to the process of evaluating environmental vulnerability (Burger, 1997). However, the mechanism of vulnerability evaluation varies from region to region because of regional environmental differences. Therefore, developing a location-based set of indicators that are suitable for the actual situation of each case study is necessary, because no universally applicable indicators currently exist (Beroya-Eitner, 2016). Additionally, knowing how to correctly convert data from multiple sources, such as data related to climatic conditions, land cover, and socio-economic condition, into an integrated evaluation index is also important for vulnerability evaluation (Munda et al., 1994). A variety of methods have been developed to evaluate vulnerability such as the fuzzy theory approach (Enea and Salemi., 2001), or the use of grey assessment models (Hao and Zhou, 2002), the artificial neural network approach (Park et al., 2004), and the analytical hierarchy process (Li et al., 2009). However, a certain degree of subjectivity cannot be avoided in index selection and index weight determination using these methods, because all of these methods mostly rely on the prior knowledge and experience of researchers. Principal component analysis is a type of statistical analysis that can be used to reduce the dimensionality of a dataset by converting a set of observed correlated variables into a set of linearly uncorrelated variables through orthogonal transformation (Hotelling, 1933), and can reduce this subjective influence to some extent. However, when considering the difficulty in finding a spatial relationship among different factors, the integration of geographic information system (GIS) data and PCA, defined as spatial principal component analysis (SPCA), was employed here. The goal was to detect the spatial tendencies of factors and use in a wide range of environmental reasearch for investigating the relationship between different indicators (Shi et al. 2009). In this study, we applied spatial principal component analysis to assess the environmental vulnerability caused by forest degradation in the Daxing'anling region, China. We combined remote sensing image data that can frequently provide updated information for inaccessible areas, where temporal and spatial variation of environmental vulnerability evaluation is needed, with PCA.

Our study builds a regional envrionmental vulnerability index (EVI) model using remote sensing, GIS, and a quantitative method based on SPCA to evaluate the environmental vulnerability in the Daxing'anling region, China. Next, the study area was regionalized into different vulnerability levels based on the EVI values. Then, alternative measures available for improving the environmental vulnerability of each area are proposed to help forest manager conduct effective forest resource management.

5.2.2 Material and methods

5.2.2.1 Vulnerability evaluation framework

According to the definition proposed by the IPCC, vulnerability is a process that mutually includes the effects of the exposure, sensitivity and adaptive capacity of a system (Turner et al., 2003). When a system is subjected to perturbations or stressors, the first step is to quantify the susceptibility of the system to exposure to that type of stress, i.e., how much the ecosystem or ecosystem components are actually exposed to a particular stressor (Fig. 5.4). This can be done using a combination of environmental variables to determine the features of the ecosystem or ecosystem components that might be influenced by external disturbances.

The second aspect to be considered is the sensitivity of the system to perturbations, which refers to variables that make the system vulnerable and easily influenced by hazards. At the ecosystem level, sensitivity is treated as a measure of the instability of an ecosystem that leads to a potential vulnerability in that ecosystem (Luers et al., 2003).

The adaptive capacity of an ecosystem characterizes its ability to bounce back to a healthy state following degradation caused by exposure to a hazard, and its capacity to maintain certain structures and functions when experiencing an external disturbance. It is determined not only by the internal resilience of a system, but also by any anthropogenic improvement of that system such as an investment in afforestation.

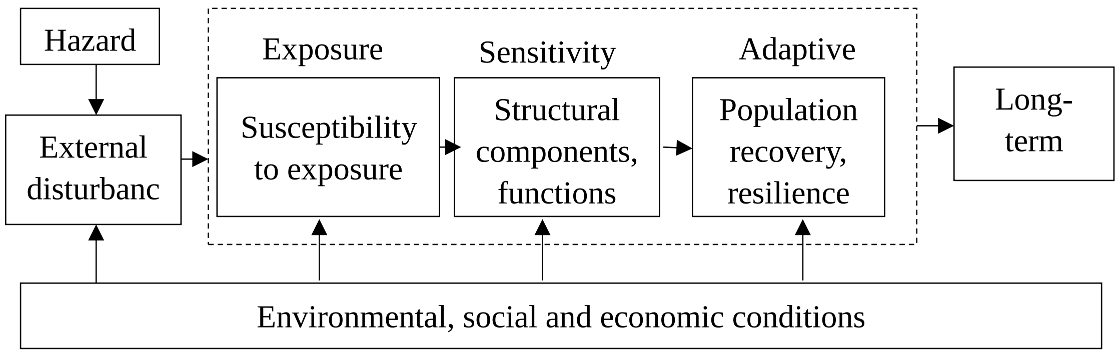


Fig 5. 4 Framework used for environmental vulnerability evaluation

Past quantitative applications used to assess environmental and climatic impacts have generally emphasized the exposure and sensitivity of an ecosystem to perturbations and stressors (Manuel and Victor., 2015; Rives et al., 2012). However, but the capacity of a system to recover from degradation has not been included in past vulnerability evaluation. In this study, environmental vulnerability was treated as a function of exposure, sensitivity and adaptive capacity, and as a collective effect of these three aspects of a system. In an ecosystem, environmental degradation might result in decreases in vegetation coverage and forest carbon storage. In addition, it also may cause degradation in soil-organic properities and influence the lives of local human residents. However, the climatic conditions, topographical features and the condition of the forest system may influence the susceptibility of an ecosystem and make it more easily affected by hazardous events. Considering data availability and local characteristics, thirteen factors were initially selected to evaluate environmental vulnerability in the present study. These included exposure (vegetation coverage, soil organic matter, population density and forest volume), sensitivity (standardized precipitation index, degree of forest fragmentation, average monthly temperature, slope gradient, elevation and proportion of vulnerable people in the population (those under 15 and above 60 years old)), and the adaptive capacity (annual investment for forest protection, literacy rate and per capita income). Exposure has a positive relationship with environmental vulnerability, meaning higher exposure leads to greater environmental vulnerability. Sensitivity responds similarly, with higher sensitivity resulting in increased environmental vulnerability. In contrast, the adaptive capacity of a system is negatively correlated with vulnerability; therefore, higher adaptive capacity corresponds to lower vulnerability.

5.2.2.2 Data acquisition and processing

This study used climatic, topographic, demographic and economic data. The climatic data were obtained from the Chinese Meteorological Data Sharing Service System (http://cdc.cma.gov.cn) that covers five national meteorological stations in the study area. The temperature and standardized precipitation indices were calculated at each of these five meteorological stations. These data were then interpolated in ArcGIS 10.2 using an ordinary Kriging method to obtain a grid dataset for the entire study area. The topographic variables were extracted from a digital elevation model with 90 m resolution that was freely available for download from the Consortium for Spatial Information Center of the Consultative Group for International Agricultural Research (CGIAR-CSI) (http://srtm.csi.cgiar.org). The demographic and economic data were derived from the Daxing’anling Statistics Bureau at the Forestry Administration Unit.

Vegetation coverage was expressed using the Normalized Difference Vegetation Index, which was derived from the Moderate Resolution Imaging Spectroradiometer vegetation product at a resolution of 250 m. All factors were preprocessed using ArcGIS (Fig 5.5). This included re-projection to the Albers projection system with parameters of the 1st standard parallel of 25, the 2nd standard parallel of 47, and the central meridian of 105, which is suitable for studies in China. A grid with 10 km × 10 km cells was then generated using the Hawth's Tools (v3.27) extension (Beyer, 2004) in ArcGIS. The mean value of each variable was extracted for each grid cell, with each grid cell treated as a study unit.

To remove the influence of unit differences among different variables, Eq. (1) was applied to acquire a dimensionless evaluation dataset:

$$Y_{ij} = \frac{x_{ij} - x_{min,j}}{x_{max,j} - x_{min,j}} \times 100\% \qquad \text{(Eq. 1)}$$

where, Y_{ij} is the standardized value of variable j in grid cell i varying from 0 to 1, x_{ij} is the measured value of variable j in grid cell i, and $x_{max,j}$ and $x_{min,j}$ are the maximum and minimum values of variable j in grid cell i, respectively.

5.2.2.3 Spatial principal component analysis

When constructing a comprehensive evaluation index during a vulnerability evaluation, it is essential to integrate a range of variables with different sources such as variables related to climatic conditions, vegetation coverage, and demographic characteristics (Munda et al., 1994). The wide use of remote sensing data and GIS provides a useful framework for integrating a variety of spatial data and addressing spatial analyses of environmental problems (Arianoutsou et al., 2011). Our study employed an SPCA approach to develop a model used to evaluate environmental vulnerability, for which the original data attributes were transformed into a new multivariate attribute set rotated with respect to the original space. SPCA is often useful when the existence or nature of the components are not known in advance (Ding, 2003).

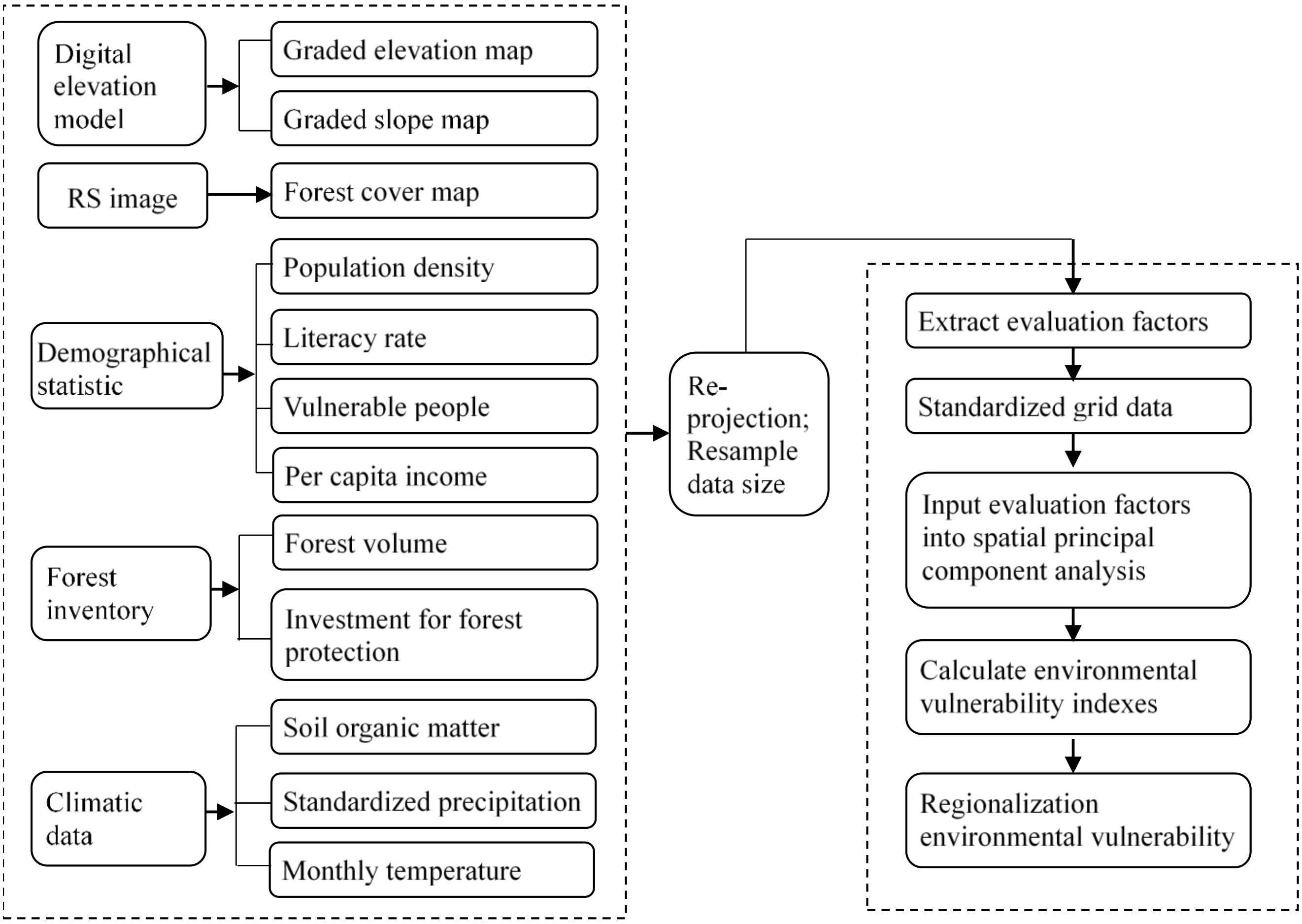


Fig 5. 5 Schematic representation of environmental vulnerability evaluation through spatial principal component analysis

The principal components were selected based on the fact that the first principal component represents the greatest amount of variance in the data. If the accumulated variance represents over 80% of the total variance, the remaining components can be ignored. The final evaluation value was obtained using Eq. (2):

$$E = r_1Y_1 + r_2Y_2 + r_3Y_3 + \cdots + r_nY_n \qquad \text{(Eq. 2)}$$

where E is the integrated environmental vulnerability index (EVI), r_n represents the contribution ratio of principal component Y_n, and n is the significant number of principal components that remain. The contribution ratio r_i was obtained using Eq. (3):

$$r_i = \frac{\lambda_i}{\sum_{i=1}^{m} \lambda_i} \qquad \text{(Eq. 3)}$$

where λ_i is the eigenvalue of the ith principal component.

In principal component analysis, the principal components are selected by eigenvalues. Generally, an eigenvalue is treated as an indicator reflecting the explanatory power of each variable. If the eigenvalue is greater than 1, it is reasonable to believe this number of components can explain the information carried by the original variables (Li et al., 2006).

In this study, the indices of exposure (*E*), sensitivity (*S*) and adaptive capacity (*AC*) were analyzed separately; then, a comprehensive *EVI* was calculated using the SPCA model. The principal components with eigenvalues greater than 1 were extracted with PC loading rotated for the maximum variance, and three principal components were identified for exposure analysis that accounted for approximately 91.4% of the total variance (Table 5.3). Similarly, three and two principal components were extracted for sensitivity and adaptive capacity analyses, respectively, using the same rule. Finally, a total of five principal components were extracted to calculate the comprehensive *EVI*. Eqs. (4)–(7) provide the linear formulae for each respective evaluation index:

$$E = 0.4508 \times E_{PC1} + 0.2941 \times E_{PC2} + 0.2551 \times E_{PC3} \quad \text{(Eq. 4)}$$

$$S = 0.4012 \times S_{PC1} + 0.3568 \times S_{PC2} + 0.242 \times S_{PC3} \quad \text{(Eq. 5)}$$

$$AC = 0.4944 \times AC_{PC1} + 0.5056 \times AC_{PC2} \quad \text{(Eq. 6)}$$

$$EVI = 0.2988 \times EVI_{PC1} + 0.236 \times EVI_{PC2} + 0.1606 \times EVI_{PC3} + 0.1542 \times EVI_{PC4} + 0.1503 \times EVI_{PC5} \quad \text{(Eq. 7)}$$

where E is exposure, S is sensitivity, AC is adaptive capacity and *EVI* is environmental vulnerability index. $E_{PC1} - E_{PC3}$, $S_{PC1} - S_{PC3}$, and $AC_{PC1} - AC_{PC2}$ are principal components for exposure, sensitivity, and adaptive capacity analyses, respectively. $EVI_{PC1} - EVI_{PC5}$ are principal components for the comprehensive environmental vulnerability evaluation; a higher *EVI* value indicates a relatively vulnerable environment situation.

In forest management process, in order to improve the effectiveness of practical countermeasures, a gradation of environmental vulnerability is needed (Nguyen et al., 2016). In the present study, natural break classification (NBC) was used to regionalize environmental vulnerability into several vulnerable regions. An NBC will group similar values and maximize the difference between classes (Apan., 1997). This is considered an objective and reasonable measure that can be used to explore the statistical distribution of clusters and classes, and was conducted using ArcGIS 10.2.

5.2.3 Environmental vulnerability evaluation

Based on Eqs. 4–6, indices of exposure, sensitivity and adaptive capacity, respectively, for the Daxing'anling region were calculated. Fig. 5.6 to Fig. 5.8 illustrates the spatial distribution of the exposure, sensitivity and adaptive capacity indices respectively, which showing that the overall exposure is not very high, with a highest value of approximately 0.27. Additionally, the central Daxing'anling had the highest exposure value perhaps because this highly urbanized region has a relatively high population density and the abundant forest cover of this region has also led to relatively high exposure. As such, a large proportion of the environmental components could be damaged by external disturbances that may occur in this area.

The sensitivity situation of the study region is a little high, with a highest value of about 0.54 (Fig. 5.7). The highest sensitivity values occurred in the southern and western areas, indicating they are comparatively the most sensitive in the region to external stressors and are relatively likely to be affected by disturbance. The climatic conditions, topographic features and forest composition makes this area susceptible to environment change.

Meanwhile, the total adaptive capacity was not very high and peaked at approximately 0.35. The ecosystems in the central and southern parts of the analysis area had the largest adaptive capacities, suggesting that these ecosystems can cope with a hazardous event or disturbance, and might respond in ways that could allow them to maintain essential functions. The low per capita income and low investment in forest protection caused the eastern area to have a relatively low adaptive capacity. However, the low exposure and low sensitivity cause this area to have a low vulnerability value, meaning the environment is in relatively good condition. The high sensitivity, relatively high exposure level and low adaptive capacity in Xinlin County combined to lead to a relatively high vulnerability value given the negative correlation between adaptive capacity and environmental vulnerability as well as the positive correlation between vulnerability and both the levels of exposure and sensitivity.

Using equation (7), we obtained the integrated environmental vulnerability index across the whole area. As showed in Fig. 5.9, the highest EVI value in the Daxing'anling area was approximately 0.86, located mainly in southern and central regions (Xinlin District and part of Mohe County). The higher EVI value indicates more serious environmental vulnerability and countermeasures against vulnerability should be proposed to improve the state of the environment in these areas. The lowest vulnerability value was approximately 0.036 in the eastern area of Daxing'anling (Huma County and part of Huzhong District). While this area is less vulnerable to hazardous events at present, it is also a potentially vulnerable region that should be monitored for any changes to forest quality.

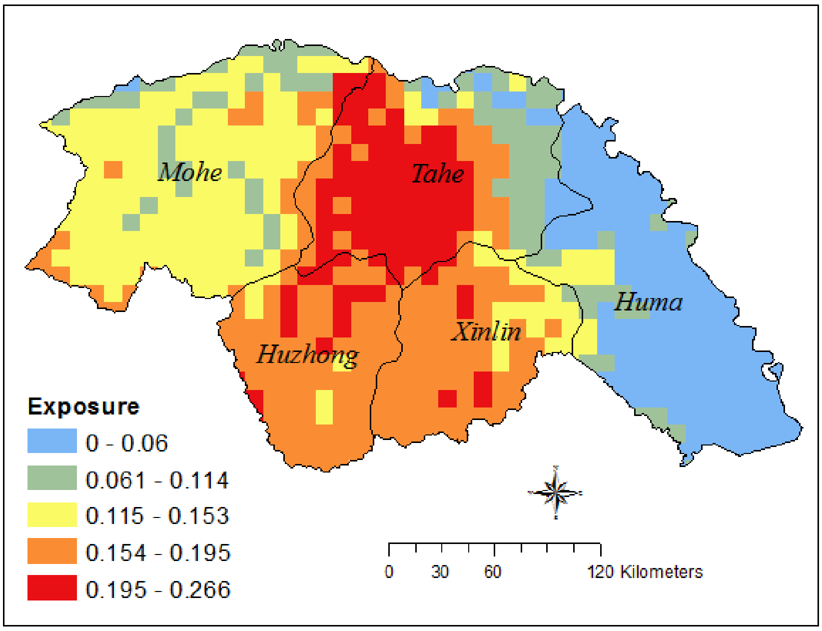


Fig 5. 6 Spatial distribution of regional exposure in the Daxing'anling study area. Higher values are represented by red color.

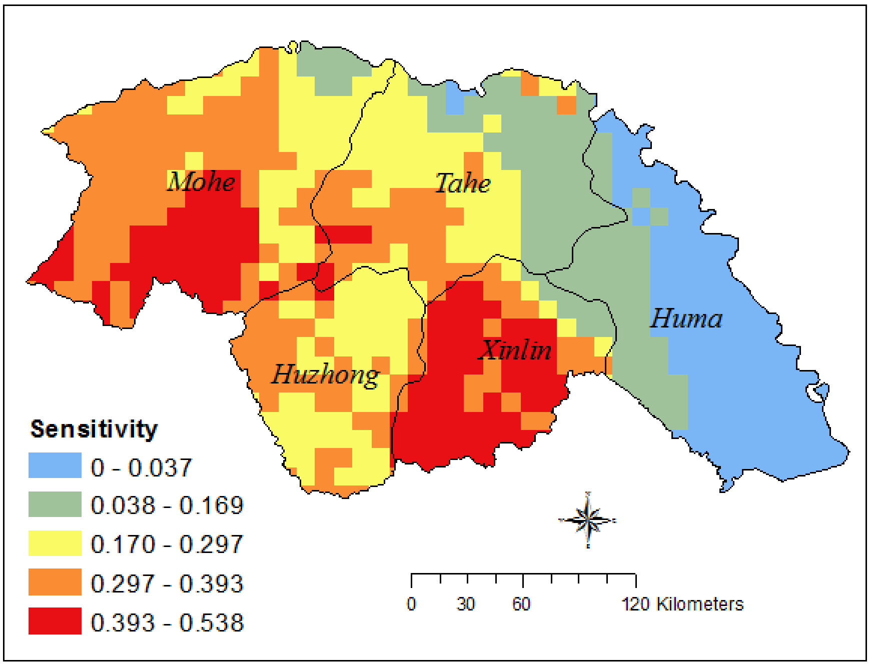


Fig 5. 7 Spatial distribution of sensitivity in the Daxing'anling study area. Higher values are represented by red color.

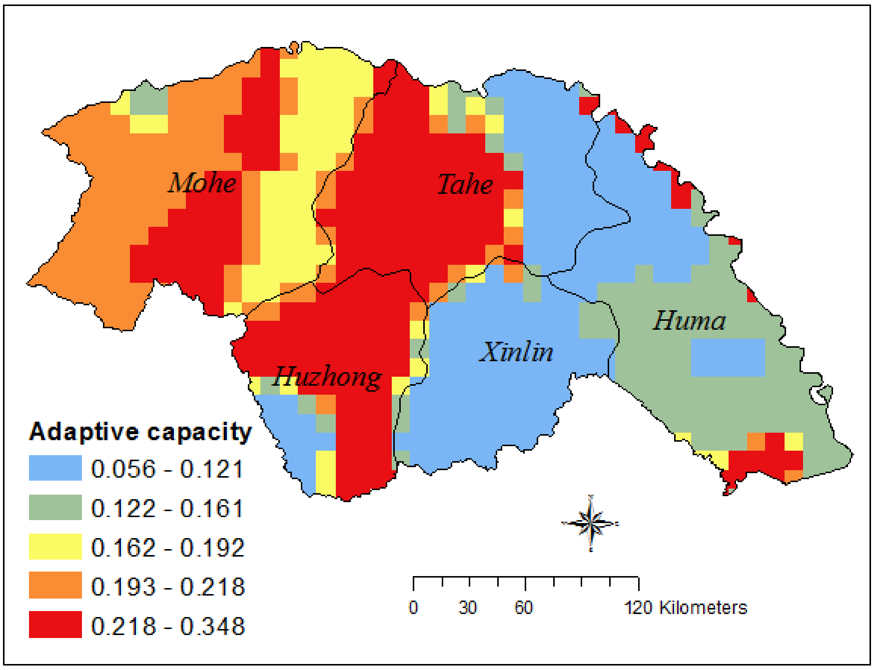


Fig 5. 8 Spatial distribution of adaptive capacity in the Daxing'anling study area. Higher values are represented by red color.

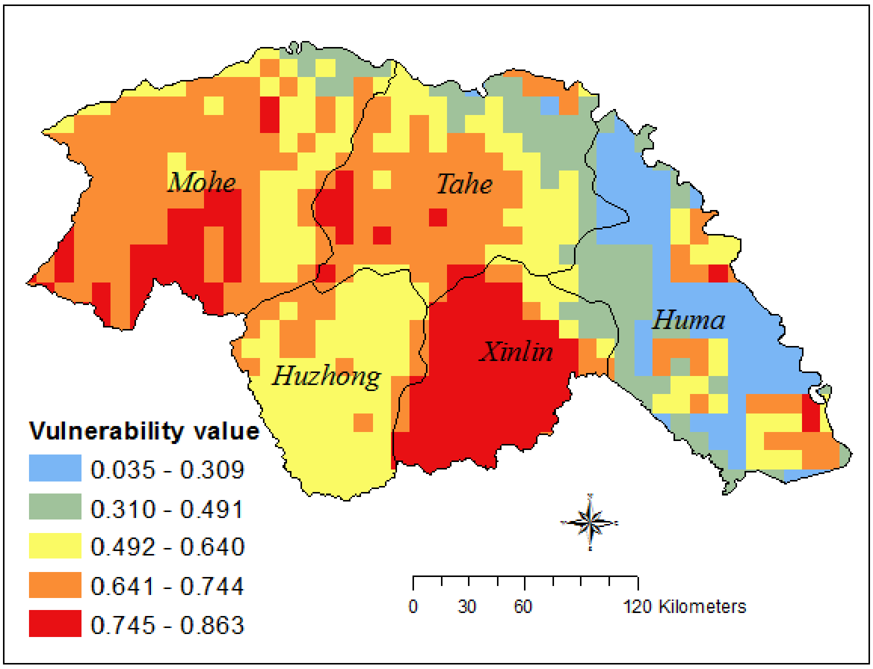


Fig 5. 9 Spatial distribution of environmental vulnerability in the Daxing'anling study area. Higher values are represented by red color.

Table 5. 3 Percentage of total variance explained by each component (PC) extracted by PC analysis.

PCs		Evaluation index			
		Environmental vulnerability	Exposure	Sensitivity	Adaptive capacity
PC1	Eigenvalue	3.117	1.828	2.147	1.153
	Contribution ratio (%)	23.974	45.709	35.778	51.081
	Cumulative contribution ration (%)	23.974	45.709	35.778	51.081
PC2	Eigenvalue	2.461	1.192	1.909	1.179
	Contribution ratio (%)	18.929	29.806	31.822	32.639
	Cumulative contribution ration (%)	42.903	75.514	67.601	83.719
PC3	Eigenvalue	1.675	1.034	1.295	
	Contribution ratio (%)	12.888	15.851	21.579	
	Cumulative contribution ration (%)	55.791	91.366	89.179	
PC4	Eigenvalue	1.608			
	Contribution ratio (%)	12.373			
	Cumulative contribution ration (%)	68.164			
PC5	Eigenvalue	1.568			
	Contribution ratio (%)	12.059			
	Cumulative contribution ration (%)	80.223			

5.2.4 Regionalization of environmental vulnerability

In this study, the *EVI* was treated as an integrated index to a regionalized study area. Considering the regional characteristics and practical needs for environmental protection, Daxing'anling is spatially divided into five regions with levels of different vulnerability: potential, slight, low, moderate and high vulnerability regions (Fig 5.10).

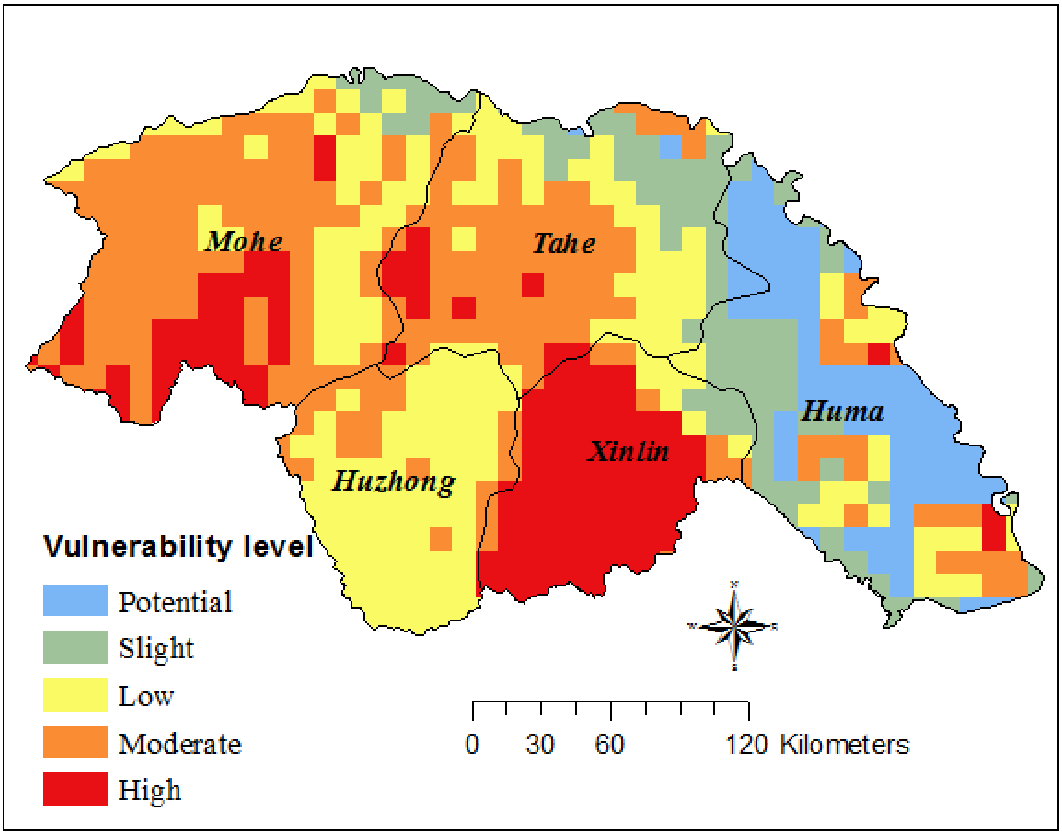


Fig 5. 10 Regionalization of the environmental vulnerability index (EVI) in the Daxing'anling study area

Based on this classification, the potentially vulnerable areas covered approximately 6.47% of the study area (Table 5.4). At this level, the ecosystem can be treated as stable, with an extremely high anti-interference ability and the capacity to recover from disturbance. Therefore, there is no need for extra measures in this area. The low vulnerable area accounted for a relatively large proportion (30.27%) of the study area. At that level the ecosystem is relatively unstable with a low anti-interference ability. The high vulnerable area covered approximately 20.88% of total study area, and can be described as an unstable ecosystem with a low anti-interference ability for disturbance. This means that if the ecosystem suffers a threatening disturbance, it would be difficult to recover and might undergo losses. Therefore, extra measures should be implemented to improve the fragile environment in those areas.

Table 5. 4 Proportions of the five environmental vulnerability levels attributed to the Daxing'anling study area.

Environmental vulnerability level	Area (km2)	Percentage (%)
Potential	4176.3	6.47
Slight	9574	14.82
Low	19550.8	30.27
Moderate	17806.7	27.56
High	13486.8	20.88

5.2.5 Function of environmental vulnerability regionalization

To help decision makers propose alternative treatments and make those treatments effective in improving environmental quality, the measured environmental vulnerability in the present study area was categorized into three sub-regions (Fig 5.11): heavy, medium and potentially vulnerable regions. These three sub-regions have different levels of vulnerability and land managers should implement three different kinds of protection measures.

Regions with heavy vulnerability: Collectively, this region mainly occurs in Xinlin District and Mohe County, and constitutes 23.9% of the total area. It is mainly located at high elevations where rehabilitating the forest trees after disturbance would be difficult. Considering this level of environmental vulnerability, this region should be strictly protected from timber harvest and funding should be made available for forest fires mitigation as needed. In addition, ecological restoration measures also should be strengthened at the same time.

Region with medium vulnerability: This widely distributed region with a medium level of vulnerability accounts for 52.3% of the total area, including Huzhong District, the majority of Tahe County and part of Mohe County. This region requires improved implementation of forest conservation alternatives. Because the Huzhong Nature Reserve serves as an important recovery area that protects rare species of flora and fauna, large-scale reforestation and a reasonable and sustainable project related to forest resources use should be formulated. Meanwhile, active participation of the local people in the environment protection area should be promoted.

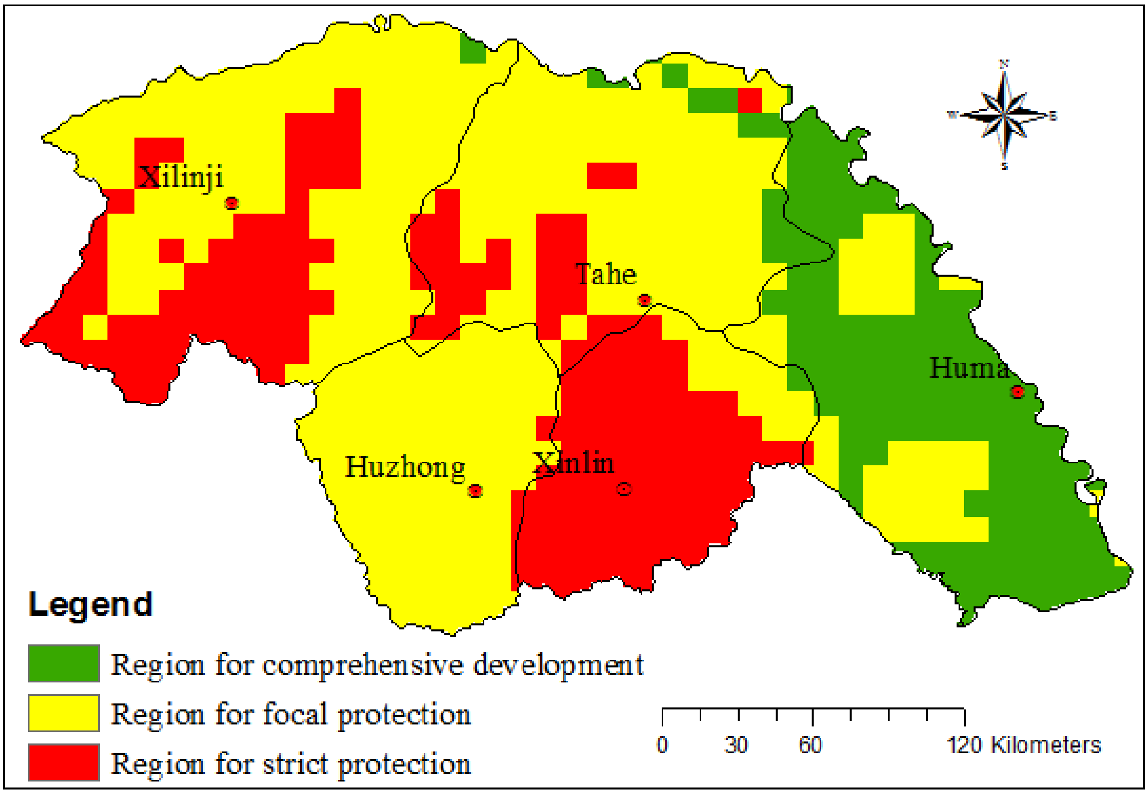


Fig 5. 11 Regional classifications for comprehensive development as well as focus and strict protection, based on the EVI.

Region with potential vulnerability: This region occupies 23.8% of the total study area. The majority of Huma County has a very low vulnerability value, which means the environment is a relative stable and the integrity of the region is intact. However, to prevent future environment degradation, a composite development program should be developed for this region. Establishing an environmentally-sound and sustainable economic compensation mechanism is a very important method that should be implemented to regulate human activity.

5.2.6 Discussion and conclusion

Through the spatial principal component analysis, five principal components were retained from the original thirteen variables. Together these five principal components accounts for approximately 80.2% of the variation. The loading of each variables for the retained PCs are shown as Table 5.5. The first PC was heavily loaded on variables of elevation, soil organic, Slope gradient and Forest volume, which indicated that the topographical factor has a greatly related to the environmental vulnerability values. The second PC substantially correlated with vulnerable population, population density and climatic variables (standard precipitation and temperature). The third PC was load on forest fragmentation degree, vegetation coverage and per capita income and the forth PC was load on per capita income, slope gradient and local investment on forest protection. Here we can see the per capita income and slope gradient were mentioned twice because one variable can load on several PCs. The fifth PC was heavily load on vegetation coverage, local investment on forest protection and local literacy level.

Previous studies have developed a variety of methods that can be used to evaluate the vulnerability of an ecosystem to certain stressors, and have pointed out that the evaluation of vulnerability is an important process during risk mitigation (Hong et al., 2016; Mildrexler et al., 2015). However, these methods largely depend on expert knowledge to allocate the contribution rates for each variable. In this study, we evaluated spatial environmental vulnerability across the Daxing'anling region by integrating remotely sensed and demographic data into a SPCA model, which can determine the contribution of each factor based on coefficients of linear correlation to reduce subjective influences on the result. Using an environmental vulnerability framework for analyses, variables related to exposure, sensitivity and adaptive capacity were selected to build a vulnerability index that was used to describe the environmental situation.

Table 5. 5 Retained principal components for the spatial analysis of total environment vulnerability assessment

	PC1	PC2	PC3	PC4	PC5
Elevation	0.402	-0.057	-0.287	0.058	0.119
Soil organic	0.407	0.186	0.019	-0.047	0.145
Forest volume	0.289	-0.003	-0.474	0.101	-0.209
Vulnerable population	-0.071	0.47	0.189	0.240	0.09
Population density	0.203	0.481	0.091	-0.183	0.091
Standard precipitation	-0.317	0.285	-0.264	0.186	0.291
Temperature	-0.436	0.268	-0.165	0.124	0.238
Forest Fragmentation	0.279	0.123	0.317	0.296	-0.327
Vegetation coverage	0.085	0.157	0.409	0.073	0.299
Per capita	0.127	-0.356	0.339	0.432	-0.058
Slope gradient	0.368	-0.094	-0.291	0.599	0.199
Local investment	0.167	-0.475	0.011	0.312	0.429
Literacy level	0.064	-0.187	0.291	-0.599	0.572

We found that the measure of vulnerability was unevenly distributed spatially across the study area. The southern and western areas had a relatively high vulnerability rating of 0.8 that was caused by the high level of exposure and sensitivity in these regions. The opposite was true for the eastern region that was associated with a low vulnerability value of 0.036 because of the low levels of exposure and sensitivity as well as the relatively high level of adaptive capacity. The southern region stands at a relatively high elevation, which led to relatively low temperatures and slow growth in the trees. Therefore, this ecosystem is vulnerable to climate change and forest fire disasters. If these forest ecosystems were heavily degraded by fire or timber harvest, restoring them back to their original state would be quite difficult. The central part of the study area is the center of Daxing’anling region, with a large human population and concentrated urbanization. However, the high exposure and relatively high sensitivity of this area were mitigated by high adaptive capacity, resulting in a medium vulnerability value for the central region. To assist land managers in proposing specific measures related to environmental protection, NBC was then applied to divide the study site into five sub-regions based on the local vulnerability indices. The lightly vulnerable regions accounted for a relatively large proportion (approximately 30%) of the total area, while the highly vulnerable regions occupy approximately 21% of Daxing'anling. Different environment management measures were suggested for each area based on the vulnerability regionalization.

This study illustrated that the integration of remote sensing, geography information system and spatial principal component analysis allows researchers to quantitatively evaluate environmental vulnerability in a region. In addition, the results of the environmental vulnerability evaluation may be helpful for decision makers by providing a more rational decision making tool for developing effective and sustainable forest resource management methods.

Chapter 6 Sustainable forest management based on comprehensive environmental risk assessment

In this chapter, the comprehensive environmental risk assessment was conducted based on the previous hazard analysis and vulnerability evaluation. By multiply the probability of forest fires occurrence and the environmental vulnerability, an integrated environmental risk value can be calculated. In order to rank the environmental risk levels, risk matrix was applied to get a qualitative evaluation of environmental risk distribution. In this research, the environmental risk was graded into four levels: potential, light, medium and high level. Correspondingly, in order to reduce environmental risk, kinds of countermeasures was proposed and recommendation for sustainable forest management was also discussed, which might provide the scientific foundation for decision-makers to improve the effectiveness of forest managements.

6.1 Comprehensive environmental risk assessment

Environmental risk assessment is the formal process to evaluate the potential consequence of a hazard event and their occurrence probability (Suter, 1993). Assessing a risk involves an analysis of the consequences and likelihood of a hazard event, which have been analyzed in the previous chapters. The process of environmental risk assessment can be summarized as follows.

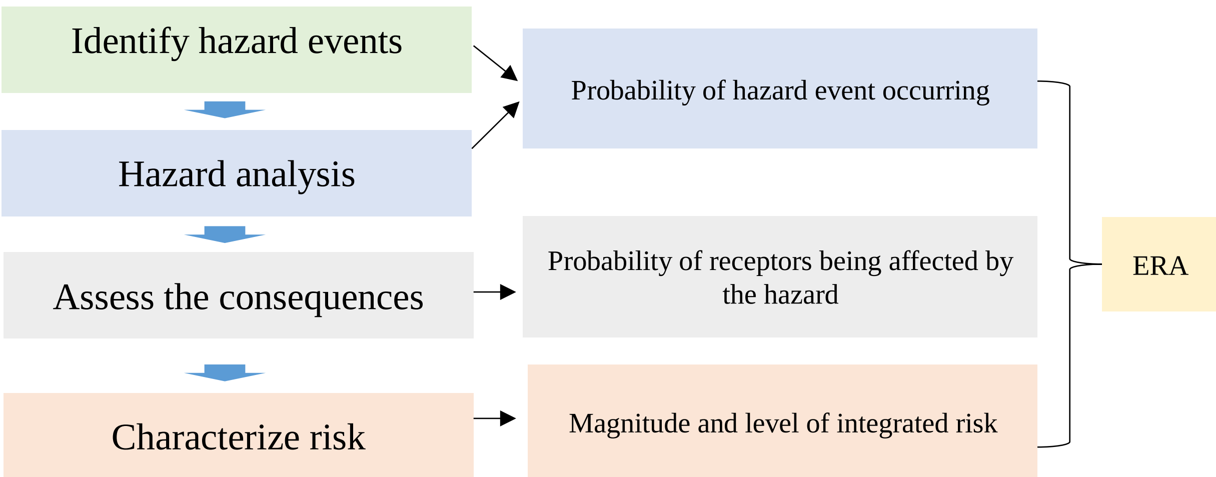


Fig 6. 1 The primary stages of environmental risk assessment.

Risk characterization is the final step of risk assessment, which pulls together the information of hazard occurrence and potential effects. It concerns with determining the likelihood of occurrence and potential adverse effects in a quantitative way, along with acknowledging the assumptions and uncertainties in risk management (Walker et al., 2003). It helps the environmental managers to address the problems (Fig 6.1) such as: (1) The probability of the hazard event occurring. (2) The probability of the environment being influenced by the hazard. (3) The magnitude of the total environmental risk and its distribution across the whole area.

A wide range of qualitative and quantitative methods have been involved in risk assessment, including fault tree analysis, event tree analysis, Markov models (Khan et al., 2015; Mandal & Maiti, 2014). Risk matrix, a semi-quantitative risk assessment approach, is a practical tool for risk ranking and management, and currently is commonly utilized in space and chemical processing industries (L. Lu et al., 2015). The risk matrix aims to rank and prioritize risk for the benefit of environment managers (Duijm, 2015). Normally, two basic methods were employed to establish categories in a risk matrix: quantitative risk score calculated through ordinal numbers (Flage & RØed, 2012) and subjective judgements called "IF-THEN" method (Markowski & Mannan, 2008). In this research, quantitative risk scoring approach displaying the basic properties of "likelihood" and "consequence", of forest degradation. In the previous chapter, the probability of forest degradation and environmental vulnerability evaluation were conducted. Therefore, linear scales was utilized to obtain the risk score by multiplying category ordinal numbers (Duan et al, 2016). The increase in the number of probability and vulnerability level might improve the resolution of final risk gradation (Markowski & Mannan, 2008). Generally, risk level cells in the risk matrix are distributed symmetrically as shown in Fig 6.2. The different risk levels are depicting in different colors: red color usually marks the high risk level at a dangerous situation, yellow and orange indicates light and medium risk level that can be reduced, green typically represents acceptable risk levels.

		Consequence (Vulnerability level)			
		V1	V2	V3	V4
Likelihood (Probability of hazard events)	H1	ERI$_{11}$	ERI$_{12}$	ERI$_{13}$	ERI$_{14}$
	H2	ERI$_{21}$	ERI$_{23}$	ERI$_{24}$	ERI$_{25}$
	H3	ERI$_{31}$	ERI$_{32}$	ERI$_{33}$	ERI$_{34}$
	H4	ERI$_{41}$	ERI$_{42}$	ERI$_{43}$	ERI$_{44}$

L1	Potential risk—Environment is in good condition and the environmental risk level is negligible that can be
L2	Light risk—Environment situation is good, with a light risk that might lead to environment deterioration.
L3	Moderate risk—Environment quality is declining. A medium environmental risk was detected.
L4	High risk—Environment is in a dangerous condition.

Fig 6. 2 Levels of concern 4 × 4 risk matrix for Daxing'anling

In the previous chapter, the hazard level and vulnerability level was divided into four different level, therefore, by multiply the level numbers of hazard and vulnerability, we can get a risk score from 1 to 16. Through the risk matrix above, the risk can be divided into four levels: potential, light, medium and high (Fig 6.3).

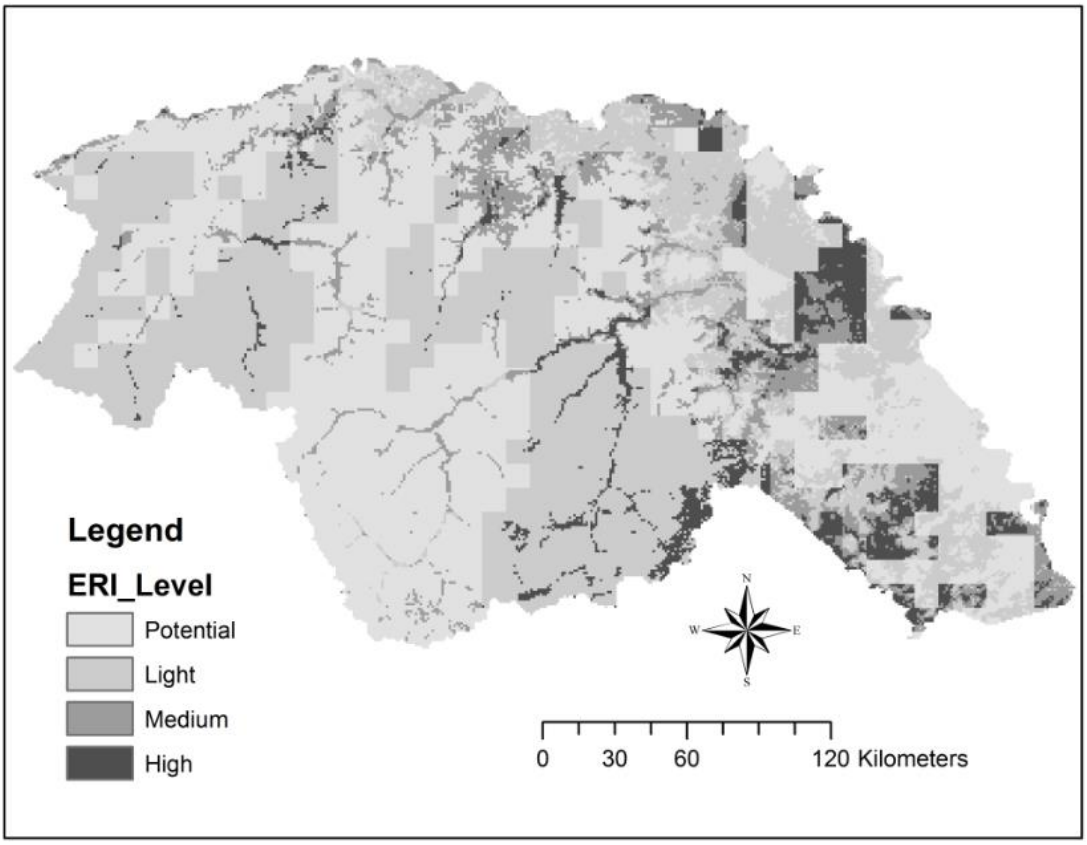


Fig 6. 3Environmental risk level distribution across the study area

From figure 6.3, we can understand that the overall integrated environmental situation is quite well. Area with a high environmental risk level occupies a small proportion, approximately 6.3% of the total area, and locates at the eastern part. The majority of the study area is in potential risk level, accounting for 41.9%. Additionally, the medium risk region accounts for approximate 41.8%. Although the potential risk can be ignored in risk management process, the protection treatment also should be implemented in order to prevent the degradation.

6.2 Recommendation for sustainable forest management

In the decision making process, the incomplete or incoherent information might limit the ability of environmental managers to make appropriate decisions (Suter et al., 1999). Therefore, the final objective of environmental risk assessment is to assist decision making process by evaluating risks of adverse effects on environment ecosystem and human livelihood. The risk management in order to reduce environmental risk can be proposed based on the risk levels. Moreover, the hierarchy risk treatment makes sure that the treatment is the best alternative for sustainable management.

Theoretically, environmental risk can be managed in two ways: reducing likelihood of hazard event and consequence. In fact, in the northeast China, the natural forest protection program has been successfully implemented in order to diminish the timber harvesting amount and has got some achievements. During the research period, the environmental risk mainly referred to the risk caused by forest fires and its potential losses. Thus, when thinking about operational forest management countermeasures, the treatments for lowering probability of forest fires and improving the vulnerable situation should be recommended.

In the previous chapter, six variables including topographic factor (slope gradient, river density and land cover type), climatic factors (wind speed) and human related factors (population density and distance from residential area) were identified as evidential factors influence forest fires occurrence. Therefore, in order to reduce probability of forest occurrence, treatments related to improve the situation of these variables should be taken into consideration. The thick foliage on the ground provides enough combustible fuels for forest fires, meanwhile the frequent human activities around the residential area for taking firewood and other goods increase the risk of ignition. Considering this, biomass technology which can transfer the combustible foliage into other kind of fuels that can be used for household’s living. Other kind of fuel treatment also be recommended in this area, for instance prescribed burning which can change the surface fuel distribution and reduce the burn severity.

On the other hand, human activities play important role in forest fires process in the study area. They can increase the ignition probability in forest fire behavior and eliminate forest fires after its occurrence together. Therefore, two kinds of treatment should be implement. One is reducing human-caused ignitions by enhancing awareness on forest fires and implementing the forest certification mechanism to increase people's consciousness on forest protection; another one is to strengthen the capability of firefighting that the forest fires can be suppressed immediately and decrease the potential losses.

As for another treatment in risk management is to reduce the vulnerability level which can minimize the impact of forest fires. In chapter five, a principal component was employed to identify factors related to vulnerability and the vulnerable regions across the study area. In the high vulnerable level area, the vulnerability level can be reduced through increasing the adaptive capacity or decreasing the sensitivity. The special economic development way which rely greatly on timber production makes the local income level is behind to other forestry area. Thus, the treatment such as economic transformation from single forestry economic to diversified economics is recommended for improve the per capital income. Investment for implementing forest restoration and establishing natural reserves to protect endangered species can help the forest ecosystem to increase adaptive capacity after impacted by forest fires.

In practical application for the proposed treatments, how to allocate the resource of protection that which region should be implement the conservation treatment first is still an existing problem in Daxing'anling area. Therefore, the final comprehensive environmental risk assessment recognized the risk level across the whole area and divided the study area into different risk level, which can be used as a prioritization basis for carrying out the forest management.

Since the risk management involves different activities including prevention, mitigation and preparedness, and recovery. In the potential risk area, the environmental risk negligible that the environment quality is good, however, prevention activities should be considered for avoidance of adverse impacts of hazardous events. In area with a light and medium risk, the environment is in a declining trend. If no treatment be taken, the environmental risk will become large. Therefore, mitigation activities should be carried out to lessen or limit the probability and adverse impacts of hazards. For areas already holds a high environmental risk, the environmental deterioration is serious and forest recovery activities should be implemented as soon as possible to improve the environment quality. Knowledge and capacities of governments, professional response and recovery organizations and individuals should be encouraged to anticipate effectively in ecological restoration from negative impacts.

Chapter 7 Conclusion and Future work

This chapter draw conclusions from the whole research. It reproduces the research aims, objectives and presents the key findings as per the four objectives. It then draws an overarching conclusion, demonstrates the original contribution of this research.

7.1 Conclusion

7.1.1 Main driving force of forest degradation

The focused environmental issue in Daxing'anling area is the forest ecosystem degradation. In this research, the literature analysis-based assumption was that the forest cover decrease such as forest converted to shrubs and non-vegetated land was seemed to be forest degradation process. In order to mitigate the decrease of natural forest, the Chinese government implemented a project named "Natural Forest Protection" to forbid the timber harvesting in natural forest area. However, forest degradation in Daxing'anling not only caused by timber harvesting, natural disturbance such as forest fires and forest insects and disease also considered to be the driving forces of forest degradation.

The objective described in chapter 3 is to find out the main cause of forest degradation in Daxing'anling. Through the literature review and the actual situation analysis, the conversion of forest land to non-vegetated land was treated as forest degradation, and the conversion from forest land to shrubs was considered as potential forest degradation risk. Remote sensing image was applied to monitor the forest cover change, results shows that the forest degradation area occupies a small proportion and sporadically distributed among the east part. By combine the settlements data, we can find that the forest degradation always occurred near the center of human activities. On the other hand, the area with risk of potential forest degradation mainly located at the east part. The degraded forest and potential degraded forest accounts for a relative large percentage of the total area, approximately reached to 10% of the total Daxing'anling.

When the forest degradation area was detected, we can realize that more attention should be paid to which regions. Through the analysis of previous literature, it can find that the forest fires plays a critical role on forest degradation process. In order to confirm this point, the relation of forest fire burnt area and forest degradation area should be analyzed. Considering the obvious spectral change caused by forest fires, spectral index called differenced Normalized Burnt Ration (dNBR) was employed to extract the burnt area. Results showed approximate 6000 km2 of forest was burned by forest fires through 2000 to 2010, and a huge forest fires occurred in 2003 burned almost 8% of the Daxing'anling. The historical statistical data of forest fires was applied to validate the accuracy of the burnt area extraction. The extracted burnt area consistent with the actual burnt area well which means this approach can be used to detect areas burnt by fires.

Overlapping in ArcGIS was used to analyze the relation between forest degradation and forest fires. The result pointed that approximate 81.28% of forest degradation area experienced at least one forest fire. Therefore, it is reasonable to treat the forest fires as the main causes of forest degradation in period from 2000 to 2010.

7.1.2 The probability distribution of forest fires occurrence

In chapter four, we attempt to identify factor contribute to forest fires and to identify regions with a high probability of forest fires. Results showed that six variables related with climate condition, topography feature, land cover and human activities were the main contributors of forest fires occurrence. The meteorological factors most strongly affecting forest fires are wind speed. The topographical factors responsible for forest fires are slope, land cover types and river density. Regarding human activities, population density and distance from residential areas are variables that influence forest fires mostly.

All of the dichotomous patterns for each variable were inputted into the Weight of Evidence model to generate the posterior probability map of forest fire occurrence. It can be seen that the zones with high susceptibility to forest fires are generally located in the east of Daxing'anling. The combined effects of meteorological conditions, topography and human activities make this region particularly vulnerable to forest fires, with a large part of it being classified as a high-risk or extremely high-risk zone. The zones with a relatively high probability (posterior probability > 0.023) of forest fires occupy approximately 4% of the total area. Zones with lower risk (posterior probability < 0.003) occupy approximately 91% of the total area and are generally located in the western part of Daxing’anling.

7.1.3 Environmental vulnerability of Daxing’anling area

In chapter five, we analyze vulnerability in the context of environment change, targeting the hazard event “forest degradation”. Our study builds a regional envrionmental vulnerability index (EVI) model using remote sensing, GIS, and a quantitative method based on spatial principal component analysis (SPCA) to calculate an environmental vulnerability value.

In this study, environmental vulnerability was treated as a function of exposure, sensitivity and adaptive capacity, and was a collective effect of these three aspects. Considering data availability and local characteristics, thirteen factors were initially selected to assess environmental vulnerability, including exposure (vegetation coverage, soil organic matter, population density and forest volume), sensitivity (standardized precipitation index, forest fragmentation degree, average monthly temperature, slope gradient, elevation and proportion of vulnerable people (under 15 and above 60)), and adaptive capacity (annual investment for forest protection, literacy rate and per capita income).

Using spatial principal component analysis, five principal components was extracted through the original thirteen factors. The first principal component greatly reflects the sensitivity of the forest ecosystem, which constructed by factor of elevation, slope gradient, forest fragmentation and standardized precipitation index. The second principal component was significant related with per capita income, population density and annual investment for forest protection. The third principal component greatly related with forest literacy rate, normalized vegetation index and forest volume.

A comprehensive environmental vulnerability index was built, which integrated the five principal components extracted by spatial principal component analysis. Through the spatial distribution, the highest EVI value in the Daxing’anling area was approximately 0.86, located mainly in southern and central regions. The higher EVI value indicates more serious environmental vulnerability and countermeasures against vulnerability should be proposed to improve the state of the environment in these areas. The lowest vulnerability value was approximately 0.036 in the eastern area of Daxing’anling. While this area is less vulnerable to hazardous events at present, it is also a potentially vulnerable region that should be monitored for any changes to forest quality.

7.2 Future work

To date, sustainable forest management is the best contribution forestry in countries which depends much on natural resource base. The dependence of China on forest resource renders it extremely vulnerable to association with highly negative social and environmental impacts. The large amount of Chinese demand on timber including domestic use and exports increased the utilization of forest resource, which imposed negative pressure on the environment ranging from increased soil erosion, reduced carbon sequestration capacity and reduced biodiversity. In the last century, forest management in China mainly focus on increased yield (economic gains) with little or no regards to environmental implications. The excessive harvesting led to an environmental deterioration that the forest quality and quantity decreased greatly.

Although in the early 21 century, the recognition of environmental importance makes Chinese government implement a series of environmental protection strategies, in which the natural forest protection program (NFPP) was designed mainly for protection natural forest resource through strictly banning selective loggings in natural forest zone. Thanks to the NFPP implementation, the rapid decline in forest quantity has been effectively improved, however, other kinds of disturbances in forest ecosystem were not paid enough attention and the prioritization for implementation of existing policy still not being discussed in the prior research.

Until now, the environmental impact assessment is commonly applied in environmental management process which attempts to evaluation the negative impact of a planning activities (Gibson, 2002; Heinma and Põder, 2010). It helps decision makers understand the possible impacts and make a decision whether to adopt the activities (Norwich, 2013). However, the effectiveness of environmental impact assessment was doubtful whether it is capable to achieve the objectives of environmental management (Noble, 2009), because many kinds of uncertainties and risks in different forms existing in environmental impact assessment (Stirling, 1999).

Given the uncertainty exists in decision making process, a risk management process was established by decision makers to guide their response to unexpected events (Zeleňáková & Zvijáková, 2017). It is relatively common to develop a risk rating approach and provide forest management direction for common disturbance agents such as forest fires and climates changes (Hirschi et al., 2001). This research presents an environmental risk assessment and rating system for forest degradation caused by forest fires based on elements of probability of forest fires and environmental vulnerability (susceptibility to forest fires). An estimation of environmental risk level was conducted through combining these elements. However, a number of reasons may cause environmental risk analysis less certain in practical application, for example, the complexity of environmental system result that the understanding of consequences of a hazard event is difficult to determine. The lack of reliable data and inaccuracies in forest inventory might resulted in a wrong evaluation and misclassification of environmental risk at some areas.

In the future environmental management process, the advantages of environmental impact assessment and environmental risk assessment should be used together to complement each other for a better decision making. They have a common ultimate goal that intend to provide sound prediction of possible consequence of planned decision (Demidova & Cherp, 2005). However, they have different emphasis in terms of substance and process. Practical application for integrating EIA and ERA can help decision makers to manage risks at the project implementation stage, meanwhile help to institutionalize the risk assessment procedure in decision support tool as environmental impact assessment.

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