UNIVERSITY OF EAST ANGLIA

Methodology and Applications of Flood Footprint Accounting For Determining Flood Induced Economic Costs Cascading throughout Production Supply Chains

ZHAO ZENG

Submitted in accordance with the requirements for the degree of Doctor of Philosophy

University of East Anglia

School of International Development

26 October 2018

Acknowledgements

My PhD is not only an amazing experience, but also a difficult journey in my life. I have confronted so many difficulties from both academic research and personal life. However, there are many people stand by me and that’s why I can finally finish this thesis with excellent achievements!

Firstly, I would like to express my deepest appreciation to my dedicated supervisor, Professor Dabo Guan, who provided me tremendous academic support and so many wonderful opportunities during my past four years. As a great supervisor, Dabo led me into the research field of climate change and economics, and offered me the scholarship for my PhD study in the UK. When I faced difficulties about the research, Dabo gave me huge encouragement and supervision in which I can feel more confident about myself. Dabo and his wife, Yuan Li, have been strongly patient and kindly to me, particular of the period when I felt so darkness of my life since my dad passed away.

Similar, I would also like to extend my deepest gratitude to my second supervisor, Professor Bruce Lankfold, for his genuine concern, important advice and encouragement. He shared me lots of experiences in both academic research and personal life, and offered me several effective guidance.

I am also hugely grateful to Professor Albert Steenge, an expert in Input-output economics, thanks very much for his academic supervision and assistance.

Special thanks to Professor Laixiang Sun and Dr Helen He, who are the examiners of my PhD viva and gave me a lot of significant comments and suggestions.

Many thanks goes to my colleges in the School of International Development, University of East Anglia and friends in the UK, for their affection, support and encouragement they had given me, especially to Dr Yuli Shan, Dr Yang Xia, Dr Zhifu Mi, Dr Jing Meng, Jiamin Ou, Heran Zhen, Mamata and Walaa. I am grateful for time spent with them during the past four years in the UK.

Furthermore, I am extremely thankful to my wonderful family and relatives, for all their love, support and encouragement. Thanks to my father, Guangming Zeng, who is the superhero in my life and never stopped loving me, for always believing in me and protecting me. Thanks to my mother, Xiaomin Chang, who is a super lady with soft and beautiful heart, for always understanding me and ready to support me. Thanks to my young sister, Zhaonan Zeng, who is a pretty princess with strong spirit, for always caring for me and sharing laughter and tears with me.

At last, I want to thanks again to my dad, I want to tell you that, I will try my best to be a great and brave person in the future life, because I know you will always be with me! I love you, dad!

Zhao Zeng

October 2018 at Norwich

Abstract

Thanks to rapid urbanization and climate change, most regions, particularly cities, are facing the risk of natural disasters and extreme weather events. Flooding, the most common type of natural disaster, has accounted for nearly 47% of all weather-related natural disasters since 1995, has killed 157,000 people, and has affected more than 2.3 billion people. Despite physical damage, floods also interrupt economic activities and result in huge and unacceptable economic costs that people cannot see directly. Thus, comprehensive analysis of the economic impact by flood disaster on the industrial and economic system has become an urgent and essential part of urban recovery and sustainable development. However, there is a lack of studies which focus on assessing the indirect economic impacts resulting from floods and thereafter providing a common quantitative approach within their assessment.

This PhD thesis presents a full methodology for a flood footprint accounting framework, so-called 'Flood Footprint Model' that can be applied to indirect economic impact assessment for both single and multiple flood disasters. The concept of 'flood footprint' is employed here to measure exclusively the total economic impact to the affected region and the wider economic systems that have been directly or indirectly caused by a flood event. Within the framework of input-output analysis, the 'Flood Footprint Model' is built upon previous contributions, with improvements regarding the optimization of available production imbalances and the requirements for recovering damaged capital. Certain factors are considered more rationally and accurately through mathematical and logical approaches, and the main novelties of the proposed methodology are: 1) a recovery scheme for industrial and household capital loss, set by endogenous factors and by considering industrial linkages; 2) a proposal for estimating degraded productive capacity constraints regarding labour and capital; 3) an optimized rationing scheme including basic demand and reconstruction requirements; 4) various extensive sensitivity analyses (as this research

proposes a more clear post-flooding recovery process based on this model scenario rather than the 'black-box' recovery in other studies).

Three practical cases are applied in order to demonstrate this method. In particular, two hypothetical example cases are used to verify the mathematical equations of the model within single and multiple flood events. Chapter 4 describes the total and indirect flood footprint assessment of a hypothetical single-flood case, in which a hypothetical flood occurs in an economy with 3 sectors; while Chapter 6 shows a flood footprint estimation of a hypothetical two-flood event that occurred in a region with 5 sectors. In addition, the 'Flood Footprint Model' is successfully applied to a real single-flood case '2012 Beijing 721 urban flooding' which affected 1.9 million people and caused a 11.64 billion Chinese Yuan (CNY) direct economic loss (Chapter 5). The total flood footprint is calculated as 21.19 billion CNY with a recovery period of 42 weeks (almost 1.18% of the total GDP in the Beijing area in the year 2012). In particular, the direct flood footprint was 11.64 billion CNY while the indirect footprint was 9.55 billion CNY; the tertiary industry accounted for 52%, the secondary industry accounted for 40% and the other 8% occurred in the primary industry. Regarding the 42 sectors, Construction, Water Conservation and Transportation were responsible for the largest flood footprint, and accounted for over 12%, 10% and 9% of the total area flood footprint, respectively. Such results seem to correspond closely with the industrial output composition of Beijing in 2012.

Aside from the modelling process being shown in three cases, a series of sensitivity analyses of the 'Flood Footprint Model' are applied to a single- and two-flood events, as actual economic data for examining the post-flood economic recovery is unavailable. Several conclusions are reached: 1) regarding the results of the indirect flood footprint of a specific flood - the higher direct flood footprint does not mean that the higher indirect flood footprint is determined by inter-linkages among industries; similarly, in a multi-flood, larger direct damage cost from each disaster will result in a larger direct flood footprint of the multi-flood, but does not mean a higher indirect flood footprint; 2) flood footprints of a given single and multiple floods are sensitive to the model-related parameters, such as labour and capital recovery paths, import and basic demand; 3) in a single disaster, delayed recovery scenarios resulting from incomplete governance show results that illustrate that delayed recovery will produce an accumulated effect that can increase the flood footprint and extend the recovery period of the whole economy; 4) in a two-flood case, the total flood footprint of a multi-flood within a given region is larger than the sum of individual flood footprints and this is the same for the indirect flood footprint, as the flood footprint is highly constrained by factors like occurrence time, and physical damage caused by the ensuing flood; 5) this model enables us to find the regional or industrial threshold for damaged capital caused by multi-flooding by calculating the maximum acceptable damage level for the first and second flood in the affected region.

Overall, the methodology improved by this thesis is more externally oriented and therefore is a better fit with reality: the final aim of the flood footprint assessment is not confined to an estimation of the economic cost of an urban flooding event at industrial and regional levels per week, month or year, but also provides more options and scenarios for post-disaster recovery management by considering the distribution of any remaining production and the allocation of financial assistance within the economic system after flooding.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Flood: A Worldwide Threat Resulting from Climate Change and Urbanization

Floods are the most common natural disasters that threaten the majority of regions at a global level and lead to numerous and unacceptable consequences, such as the 2016 Yangtze River floods in China. The flood alone resulted in over 3.1 million people being affected, the ruin of 73,000 homes and the destruction of 198,000 houses in 86 cities in 11 provinces in China; it encompassed 27 million hectares of crops, and led to a direct economic loss of up to 16.18 billion British pounds (GBP), (nearly 0.19% of the total gross domestic product (GDP) in China in 2016 (Masters and Henson, 2016)). According to estimates by the United Nations, more than 80% of cities, and over 2 billion people, are at high risk of at least one type of natural disaster (DESA, 2016, UN-Habitat, 2016). Over 1 billion people rely on the floodplain throughout the world (Aerts et al., 2014). Since 1980, flood-related disasters have affected at least 2.8 billion people, causing 4.5 million to become homeless, 540,000 people have died and 360,000 people have sustained injuries (this figure excludes unrecorded injuries, estimated at 38,000 to 2.7 million). In the last year, flooding accounts for the second largest part of disaster-induced economic damage with an average annual loss of 44 billion US dollars (USD) (equal to 33 billion pounds (GBP)) (Figure 1.1), which equates to 16.8% of the total 2017 GDP in the UK. A growing number of researches that associated with environmental science and human social science illustrate the interactions between human activities and natural disasters (Strömberg, 2007). Even though humans are not able to impact directly upon the frequency and severity of natural disasters, the heightened risks of natural disasters, particularly floods, are seen as ‘feedbacks’ that result from climate change and urbanization (IPCC, 2012).

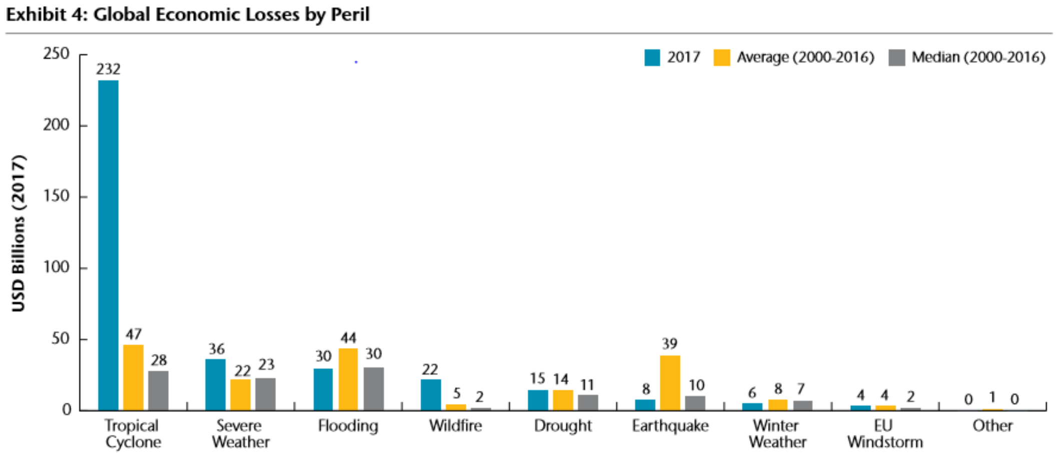


Figure 1.1. *Global economic losses by Peril, source: Benfield (2017).*

Climate-induced natural disasters account for over 93% of all the natural disasters in the world (Palmer, 2013), and the variation of weather patterns on the earth has lead to changes in natural hazards. Based on the records from EM-DAT, the total number of climate-induced disasters has doubled over the past forty years, from 3,017 events in 1976-1995 to 6,392 events during 1996-2015 (CRED, 2016). Climate change, which is a significant issue that concerns most people, mainly refers to a global high average temperature and the 'greenhouse effect' which is the main cause for this. The 'greenhouse effect' refers to the process of radiation from a planet's atmosphere that raises the temperature of the earth's surface to a level 'above what it would be without its atmosphere' (IPCC, 2014a). The majority of scientists examining climate change unanimously agree on the point that human expansion of the 'greenhouse effect' has caused the current global warming (IPCC, 2014b, Oreskes, 2004, NRC, 2011). In particular, in the Fifth Assessment Report by the Intergovernmental Panel on Climate Change (IPCC), 1,300 individual scientific experts from various countries came to the conclusion that the probability of human actions having raised the global temperature over the past 50 years is greater than 95 percent (IPCC, 2014b). From an environmental perspective, a warmer planet is probably creating more evaporation and precipitation, causing water vapour, the most abundant greenhouse gas, to react physically or chemically to the dynamic temperatures. In addition, thanks to the greenhouse effect, warmer oceans, coupled with melting ice and glaciers will increase sea levels (NASA, 2018). Thus, some regions will suffer with more water and others will become dryer. As a result, the occurrences of natural disasters, primarily of extreme water-related disasters, (including floods and severe storms) will become more frequent worldwide (IPCC, 2012, Visser et al., 2014, Winsemius et al., 2016, CRED, 2015b, Nordhaus, 2010, Aerts et al., 2014).

Rapid urbanization also raises the risk during natural disasters as a growing amount of people will be exposed to the disasters, particularly when they hit cities. The great opportunities that are offered by urbanization are attracting more and more people to move to the urban areas. According to records, urban inhabitants represented nearly 54.5% of the global population in 2016 and this number will increase to 60% by 2030 (UN-Habitat, 2016). This means that in 2030, cities with over 1 million inhabitants will account for one in every five people. Meanwhile, both the size and number of cities in the world are growing all the time. Megacities, whose inhabitants exceed 10 million, are projected to increase from 31 with 500 million people in 2016 to 41 with 730 million people by 2030 (DESA, 2016). Alongside the population density in urban areas, the location of these cities is another reason which increases the risk of disaster. Globally, around 15% of cities are located along coastlines, these being the regions that frequently suffer the high risk of more than one type of natural hazard, particularly floods and cyclones. Moreover, Asia and Africa have developed most of the fastest growing cities worldwide during the past 15 years. Nearly 47 cities show increasing population trends with an annual growth excess of 6% since 2000 - 6 of these cities are in Africa, 40 are located in Asia (20 in China), and the other one is in Northern America (Shepherd et al., 2013). The lower the level of development within the city, and therefore the lack of financial assistance, the higher the risk from natural disasters (Alexander, 2017, Palmer, 2013). Cities, in particular megacities, are consequently becoming more sensitive to the shock of natural disasters, in particular to floods (Aon Benfield, 2017a, Okuyama, 2014, Cutter and Finch, 2008).

1.2 Flood Footprint Assessment: A New Way of Thinking about Flood-induced Economic Consequences

In this research, the concept of a 'flood footprint' is applied to characterize the total economic impact (relative to the pre-disaster level) that is directly and indirectly caused by a flood event in the region, and the wider economic system (Mendoza-Tinoco et al., 2017). The 'flood footprint' was proposed by Dabo's team (Mendoza-Tinoco et al., 2017, Li et al., 2013) and can be regarded as a comprehensive indicator of economic influence by natural disasters. The concept of 'flood footprint' only refers to tangible impacts; it measures the cost of human goods and services that were used prior to the support recovery of an affected economic system. That is, it quantifies the total cumulative economic losses, including direct and indirect economic losses, triggered by a flood event until the economy has fully recovered to the pre-disaster level. The direct 'flood footprint' is the economic impact and/or loss caused by direct consequences of flood events, and refers to the short-term physical impacts on natural resources, people and tangible assets (Nations, 2010). The indirect 'flood footprint' is the economic impact/loss resulting from flood-induced labour delay, capital loss, disruption of economic activities in the whole production supply chain and costs for physical capital reconstruction (Hallegatte, 2008, Baghersad and Zobel, 2015). Compared with other concepts related to flooding damage, like economic impact and economic loss, 'flood footprint' is not only able to provide the amount of the economic loss, but also shows us the modelling recovery routes of the affected economic system on an industrial and economic level (Mendoza-Tinoco et al., 2017). Similarly with the 'flood footprint', the economic consequences caused by other natural disasters, can also be measured with the relevant disaster footprint, such as a storm footprint or hurricane footprint.

There are two reasons that this research has adopted the indicator of 'flood footprint' to describe the total economic consequences caused by flood disasters. Firstly, the concept of a 'footprint' has been introduced in many studies and used to track the interconnection between nature and humans (Rees, 1992, Hoekstra and Hung, 2002, Wiedmann and Minx, 2008). For example, the most widely known footprint-associated concept, the ecological footprint, proposed by William Rees in 1992 and employed to measure human demand on natural capital (Rees, 1992), has been defined as "the biologically productive area needed to provide for everything people use". This is followed by the carbon footprint which is a measure of the total amount of carbon dioxide and methane emissions of a given population, system or activity by considering all related sources, sinks and storage (Wright et al., 2011). Water footprint indicates the volume of fresh water consumed and used to assimilate pollution (Hoekstra et al., 2011). Further, and different to the footprints referred to above (which mainly illustrate human impacts on natural resources and ecosystem), the flood footprint reveals the flood impacts on the human economic system. Therefore, since 'footprint' demonstrates a dynamic process, flood footprint can propose a dynamic influence process, within a specific economy, during a certain affected period.

This implies that the target of the flood footprint assessment is not confined to the estimation of economic cost by a flooding event, but provides more options and approaches for post-disaster recovery management and process monitoring, by considering the distribution of the remaining production, and allocation of the financial assistance among the economic sectors or systems after this flooding. As post-disaster economic recovery is a complex and hidden process and there is generally a lack of available realistic data for validation, flood footprint assessment becomes an effective way for modelling how a flood affects the aftermath economy. Furthermore, flood footprint assessment enables awareness to be raised about natural disaster risk analysis at an industrial level and is helpful to minimise the economic impact after the same kind of natural disasters in the future.

1.3 Research Motivation

Due to climate change and rapid urbanization, more regions and populations are facing the challenges of risk caused by natural disasters such as flooding (Alfieri et al., 2017). For example, China is a country that has undergone a rapid industrialization and urbanization process. The urban population in China increased from 170 million to 670 million during the period from 1978 to 2010 and now accounts for more than 50% of the total Chinese population. More people are moving to cities in order to find jobs. Since 1995, the rate of urbanization has grown even faster than that of economic development in China (Chen et al., 2013). The majority of urban centres are located in climate-related hazardous-prone areas, with risks such as floods, earthquakes and typhoons (Baker, 2012). Such rapid urbanization has not only increased the number of city residents, but also other basic elements of an urban city, such as buildings, infrastructures and services which are now exposed to climate change and climate-induced natural disasters (Otero and Marti, 1994, Cavallo et al., 2013). From the urban economic view, climate-induced extreme events directly influence human capital and productive capital; meanwhile, urban business flows are affected as well. Therefore, more economic systems will be exposed to high risk in climate-related disasters.

Studies about natural disaster impact analysis are increasingly paying more attention to the socio-economic impacts of natural hazards, but not only on the direct impact to people and physical assets (Hallegatte et al., 2007, Steenge and Serrano, 2012, Okuyama, 2014). In the context of impact assessment of natural disasters, these initial damages constitute direct damage, and their assessment is useful both in understanding the immediate implications of damage and in marshalling the pools of capital and supplies required for rebuilding after a flooding event. Because economies and societies are coupled through complex economic networks, any small-scale damage may be multiplied and cascaded throughout the wider economic systems and social networks. The US National Research Council (1999) emphasized the importance of studying the overall social-economic impacts of major disasters because 'determining appropriate amounts of resources for victims of disasters cannot wait until after a disaster […]'. Finally, planning emergency response necessarily must precede a disaster'. An increasing number of studies show that direct economic losses are only a fraction of the total economic consequence and that the indirect economic impact plays an important role in natural disaster risk analysis and sustainable development (Baade et al., 2007, Cunado and Ferreira, 2014, Scawthorn et al., 2006a, Hallegatte and Przyluski, 2010). The total economic impact of natural disasters, especially for indirect economic impacts, however, is still poorly understood (Bockarjova, 2007, Okuyama and Santos, 2014, Okuyama, 2014, Koks and Thissen, 2016).

In addition, many studies claim that the economic consequences of disasters in developing countries are severer than those in developed countries, since the former encounter greater vulnerability (Mechler, 2004, Christoplos et al., 2001, Murlidharan and Shah, 2003, Pingali et al., 2005). At the same time, disruptions to industrialized countries should be regarded as a priority due to their increased complexity (Steenge and Bočkarjova, 2007, Morrow, 1999). Hence, more studies on the relationship between natural disasters and regional sectors and economics are required for disaster risk analysis and management in the future. A better understanding of the full economic consequences of natural hazards calls for a systematic and dynamic assessment tool to capture both its direct and indirect economic impact (Okuyama and Santos, 2014, Kellenberg and Mobarak, 2011).

Regarding the responsibility issue, Aerts, (2014, p.474) formulate this as a policy question: '*Who should pay to make NYC (or any city) more resilient to future flood disasters*?' In other words, it means 'who should responsible for the flood disasters?' In recent years, there has been a shift in flood management from 'government' to 'governance'. When referring to flood risk management in particular there is an increasing preference for the notion of 'governance' that allocates responsibilities to multiple levels or actors rather than 'government' in which one single authority makes all the decisions (Mian, 2014). However, lack of analytical approach is able to quantify the industries' responsibilities in the aftermath of natural disasters.

Hence, this work meets these concerns by undertaking to provide an effective and efficient approach for assessing flood-induced economic impacts at industrial and economic level. With adoption of flood footprint concept, this thesis will offer a methodology and applications of flood footprint accounting for determing flood induced economic costs cascading throughout production supply chains.

1.4 Research Design

1.4.1 Research Question

As described previously in Research Motivation, demands for comprehensive assessments of economic consequences of floods are imperative and necessary. For the flood-induced direct economic risk assessment, its measurements as water-depth function have already been accepted by most studies. Therefore, with information such as risk values of affected buildings or land-use types, it is easy to calculate the direct flood footprint. However, few studies cover the indirect economic impact or can quantify the indirect impact. Moreover, due to the scarcity of practical data, post-flood economic conditions are rarely mentioned. Therefore, faced with these research gaps, the primary research question here is:

"***How to measure flood induced economic costs cascading throughout production supply chains***?"

By addressing this issue, three other sub-questions are raised.

- *Which indicator is appropriate to express flood induced economic impacts?*
- *What is the approach applied for flood footprint accounting with consideration to the production supply chains?*
- *How to assess the relevant factors influencing flood footprint within an economic system?*

1.4.2 Research Aim and Objectives

This thesis attempts to explore an effective approach for flood-induced impact analysis from an economic perspective by adopting the concept of the flood footprint. In order to assess the indirect economic impact that results from either a single or subsequent flood disaster, a robust methodology framework – Flood Footprint Model – will be used. The specific objectives of this study are to:

- Provide an introduction of flood-related influences on human society in which direct and indirect impacts caused by floods are described, as well as the post-flood economic conditions.
- Present a review of the existing quantitative tools for flood-induced economic indirect impact assessment and particulars on the approaches associated with input-output models.
- Build an input-output based robust methodology (Flood Footprint Model) for indirect flood footprint accounting both mathematically and logistically, in which the approach is able to quantify both single- and subsequent-flood induced indirect economic impacts by capturing industrial and regional

interdependencies and incorporating certain factors such as damaged capital and affected labour.

- Apply the approach to both individual flood and two-flood cases, in which the flexibility of the model structure can be validated through hypothetical flood cases and the feasibility of the model can be tested through a real flood case.
- Offer several post-flood economic recovery plans to policy-makers by simulating various recovery conditions in the aftermath, such as alternative labour or capital recovery plans.

1.4.3 Research Framework

Since the flood footprint is a new indicator that has been proposed in recent years, the approach of 'flood footprint assessment' is still lacking systematization and standardization. Thus, this thesis builds a framework, shown in Figure 1.2, to provide practical guidance for flood footprint assessment in each case. Four stages are referred to in the 'flood footprint assessment' - setting goals and scope, flood footprint accounting, sensitivity analysis, and response formulation.

- **Step 1. Setting goals and scope**

In the first step, the space and time units of the flood footprint are identified. In general, this means locating the single- or multi-flood footprint within a sector, municipality, province, or nation, and other administrative or economic areas at weekly, monthly, annual or other time periods.

- **Step 2. Flood footprint accounting**

This step deals with quantification and monetization of the flood footprint by considering the direct and indirect economic consequences. This thesis focuses on indirect flood footprint accounting, in which a methodology, the 'Flood Footprint Model', is constructed for calculating the indirect flood footprint that is produced by single- and two-flood events (Chapter 3). Input-output analysis is one type of assessment tool for measuring the economic effects within an economy due to external shocks. It is able to capture the interactions between producers and consumers in a given economy and can extend to disaster-induced indirect economic impact evaluation by taking production bottleneck into account. The advantage is that it emphasizes the centre role of the basic sectors in the economy, and underlines their outstanding role in contributing to loss (Rose and Lim, 2002). Regarding the concept of flood footprint - it not only serves as an output of a specific natural disaster by indicating the amount of economic loss, but it also serves as a dynamic process in the aftermath of natural disasters that closely corresponds to the resilience of the affected economy. Consequently, with the idea of the flood footprint and the framework of input-output analysis, the indirect economic impact and dynamic post-disaster recovery can be calculated.

- **Step 3. Flood footprint senstivity analysis**

This next step assesses the probability of a flood footprint occurring in the given economy during a certain period. Due to the scarcity of practical data to express post-flood economic conditions, this step offers probable flood footprints in various scenarios through sensitivity analysis, such as alternative recovery plans for certain parameters, adaptive behaviours, different levels of governance and flood-induced capital damage.

- **Step 4. Flood footprint response formulation**

The last step formulates a response strategy. The goals of the flood footprint assessment are to assess how the flood and related disasters influence a given economic system and to provide options for mitigation of the flood-induced impact. Through analysing flood footprints at specific levels (such as sectoral, administrative and economic), relevant stakeholders or policy-makers can decide how to respond to the flood disasters and who should be responsible for post-disaster economic recovery.

Overall, the four phases of flood footprint assessment, as presented in Figure 1.2, illustrate flood footprint issues. The goals and scope of flood footprint assessment are largely dependent on research interest. The flood footprint accounting phase determines the methodology applied and the data types that need to be collected. After accounting, the sensitivity analysis phase is where a variety of alternative exogenous factors are considered and then a database is provided for the last step of 'response formulation'. These four steps are just the guidelines proposed for the application of the flood footprint. With respect to this research, the core part is the indirect flood footprint accounting (Step 2) and related sensitivity analysis (Step 3).

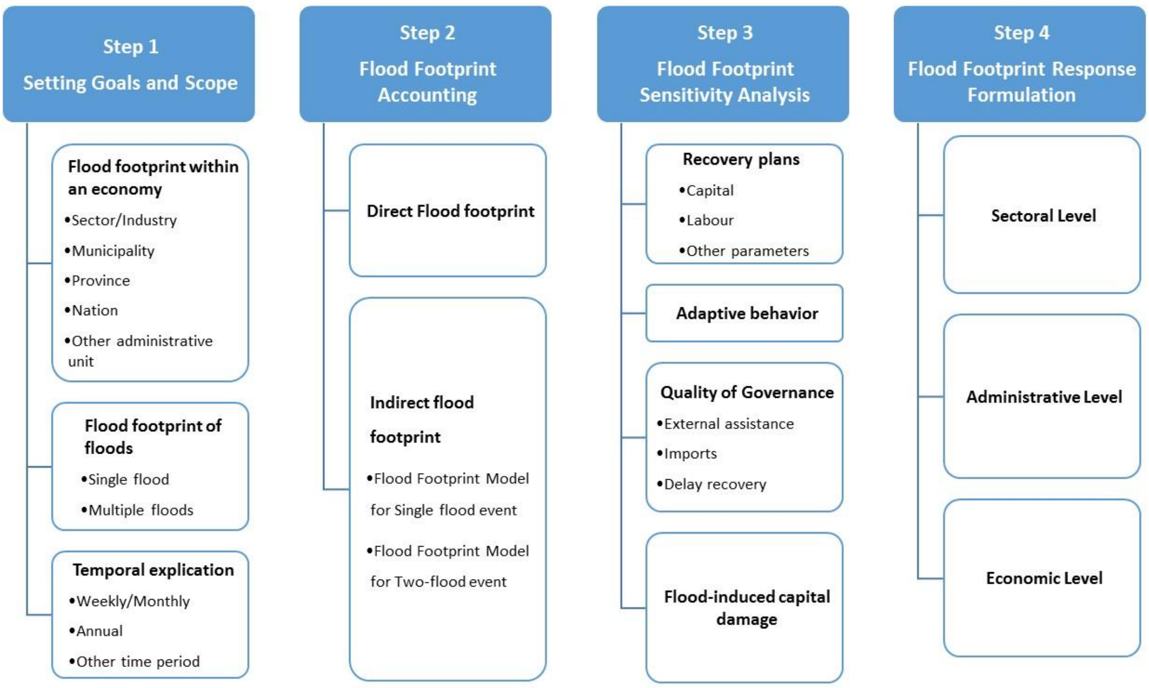


Figure 1.2. Research framework of flood footprint assessment.

1.4.4 Outline of the Thesis

This thesis is divided into 7 chapters. Chapter 1 primarily contains the research design of this thesis. Chapter 2 is a review of flood-related literatures. Chapter 3 describes the methodology developed through this study. Chapters 4 to 6 outline the applications of the methodology in which three case studies are provided. Chapter 7 sets out the final conclusions.

Chapter 1 gives a brief introduction of the research background of this thesis, including research motivation and research design. The main concept of flood footprint that is employed in this research, as an indicator to quantify the economic impact due to flooding, is defined here.

Chapter 2 presents an overview of current flood-related risk assessments by reviewing the existing literature about natural disasters. The basic definitions of flooding and natural disasters are introduced, as flooding is the most common type of natural disaster. This is followed by an analysis of flood-induced direct and indirect consequences on human society, particularly on the economic system. After a brief comparison between the diverse approaches to flood-induced indirect economic impact measurement, research gaps are identified which the study in this thesis is expected to address.

Chapter 3 describes the methodology of the Flood Footprint Model that is developed in this thesis for indirect economic impact accounting. As input-output analysis is the basic framework of the Flood Footprint Model, relevant input-output models, and their extensive applications within natural disaster risk analysis, are reviewed. Based on the contributions of these models, the proposed Flood Footprint Model is outlined. Next is the building process of the Flood Footprint Model for the single flood and two-flood disasters, using a mathematical approach. Logical explanations and model parameters are listed, such as capital and labour constraints, supply bottleneck, and rationing schemes.

Chapters 4, 5 and 6 present the results of the Flood Footprint Model for indirect economic impact accounting of a single flood event, and the applications for flood footprint assessment. Chapter 4 focuses on a flood footprint assessment of a hypothetical single-flood event within a hypothetical numerical economy (as the aim of this chapter is to illustrate the modelling process of the Flood Footprint Model), and offers sensitivity analysis approaches for probable recovery scenarios. In Chapter 5, the Flood Footprint Model will be applied to a practical single flood event. Various sensitivity analyses are presented in order to test the feasibility and flexibility of the Flood Footprint Model. Chapter 6 presents another illustration of the Flood Footprint Model, and presents a study of a hypothetical two-flood event. A detailed measurement of the flood footprint is shown and the sensitivity analysis includes factors and physical influences. In addition, an approach for assessing the regional/economic threshold for flood-induced capital damage loss is proposed.

Chapter 7 concludes with the main findings and primary contributions, policy implications, research limitations and direction for further study.

Chapter 2 Poor Measurements on Flood Induced Indirect Economic Costs

This chapter provides an overview of flood-associated issues that can be described in the form of three questions:

- What is a flood disaster?
- What are the consequences resulting from flood disasters?
- How do we measure the flood-induced economic impacts and the indirect economic costs throughout the production supply chain?

The first question (Subsection 2.1) covers the definitions of flood disasters and associated concepts - natural disaster/hazard/catastrophe and multi-hazard, in particular - and distinctions are made between rapid and slow onset natural disasters. Subsection 2.2 answers the second question, setting out the immediate and indirect ways that floods influence human society, especially with regard to the economic system. It considers the indirect economic impact as a vital part of flood-induced consequences, and reviews the idea of raising its awareness due to its close links to post-disaster recovery and management. Measuring economic impacts resulted from flood-related disasters is one of the main challenges in the disaster risk studies, the last question that demonstrated in Subsection 2.3 offers the common quantitative assessment approaches for disaster-induced indirect economic consequences analysis and compares their advantages and disadvantages. Subsection 2.4 concludes with an assessment of the research gaps in the existing flood-related literatures, with regard to indirect economic consequence assessments and post-flood economic recovery analysis in a given region after a specific single- or multi-flood event. As flooding is the most common type of natural disaster (CRED, 2015b), it is suggested that more effort should be made on assessing its indirect economic consequences.

2.1. Flood: A Common Type of Natural Disasters

Natural disasters are widely known for their disastrous effects on human beings. For example, in 1998, the Yangtze River flooded in China, leading to 4,150 people dead and 145 billion GBP lost; the 2005 Hurricane Katrina in the United States resulted in economic costs exceeding 90 billion GBP; the April 2015 Nepal earthquake killed nearly 9,000 people and injured 22,000. As the most common type of natural disaster, flooding has accounted for nearly 47% of all weather-related natural disasters since 1995 (CRED, 2015b). It seems that in research associated with natural disaster risk analysis, the term 'natural disaster', which is simply defined as 'a major adverse event resulting from natural processes of the Earth' (Wikipedia), is frequently used, as well as 'natural catastrophe' or 'natural hazard'. These terms are all used to indicate the same event in articles and reports (Cutter et al., 2008). So is there any difference between these terminologies? In order to assess flood impact, we should first ask 'what is a natural disaster?'

2.1.1. What is a natural disaster?

Natural disaster consists of two words, 'natural' and 'disaster'. The former word shows the origin of a natural disaster, and the latter illustrates its consequences. 'Natural' means that the calamity has resulted from a natural phenomenon or process (Alexander, 2017); and 'disaster' is "A serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts" (UNGA, 2016). Over time, there has been an increasing tendency to extend the impact of a natural disaster within its definition. O'Keefe et al., (1976) posited that "Disasters marks interface between an extreme physical phenomenon and a vulnerable human population", while Turner (1976) defined a natural disaster as "an event, concentrated in time and space, which threatens a society or a relatively self-sufficient subdivision of a society with major unwanted consequences as a result of the collapse of precautions which had hitherto been culturally accepted as adequate". By the 1990s, natural disasters came to be regarded more as social phenomena than a natural calamity (Bankoff, 2001, Horlick-Jones, 1995, Morrow, 1999, Schipper and Pelling, 2006). For instance, Alexander (2017, p.4) defined it as any rapid, instantaneous or profound influence that comes from the natural environment and works on the socio-economic system. By considering the human-induced system, Quarantelli (2001, p.332) defined a natural disaster as an extreme phenomena caused by the combined effect of the natural and socio-economic systems, leading to a destructive outcome. Taking into account the temporality, space and severity of impact, Bockarjova (2007, p.26) sees a natural disaster as "a discontinuity that resulted from interaction between a natural phenomenon and a human-induced system, where the system becomes adversely affected beyond the scale of minor changes, implying loss of connectivity within the established system, with well-specified spatial and temporal dimensions".

The concept 'natural hazard' is more commonly used as the manifestation of a natural disaster in American literature (Bockarjova, 2007). However, compared with disaster, natural hazard primarily considers the potential damage conditions (Benson and Twigg, 2004), and can be summarized briefly as "natural-induced impact on the human society". For example, Burton and Kates (1964) proposed that natural hazard is made of the elements from the physical environment and results in harmful impact on humans due to extraneous forces. White (1974) regarded a natural hazard as an interaction between nature and people that is controlled by both adjustment of the human use system and the natural events system. UNDRO (1982) defined a natural hazard as "The probability of occurrence within a specified period of time and within a given area of a potentially damaging phenomenon". Alexander (2017) concludes that a natural hazard is a physical event that has influences on human beings and their environment. In addition, in the terminology list from the United Nations Offices for

Disaster Risk Reduction (UNISDR, 2017), a hazard is "A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation", and natural hazards are "predominantly associated with natural processes and phenomena". It also indicates that the consequences of a disaster are more severe than a hazard, as it states that "severe hazardous events can lead to a disaster as a result of the combination of hazard occurrence and other risk factors".

A 'natural catastrophe', has been simply described as 'unusually severe disaster' (Wikipedia), due to a lack of a well-defined definition. Globally, the events that have been referred to as natural catastrophes (such as the 2004 Indian Ocean Earthquake, the 2011 East Africa Drought, and the 2015 Hurricane Harvey in the United States), threatened millions of people's lives and destroyed enormous amounts of property. Even though it is clear that the influence and scale of a natural catastrophe is much larger than a natural disaster, there are no clear criteria to distinguish a catastrophe from a disaster. However, the distinction closely responds to the vulnerability of the human-induced system. If the region, and residents in particular, are unlikely to survive and thrive in the aftermath of a natural disaster, the disaster turns into catastrophic event (Alexander, 2017). In some poor countries, if the industrial loss caused by a physical event is too large to recover from, then the event become a natural catastrophe. Bockarjova (2007) provided a better definition as, "A catastrophe is an extremely severe adverse shock, which causes a substantial disruption of the system, with well-specified spatial and temporal dimensions, to the extent that it fails to perform its vital functions for a considerable period of time, or forever."

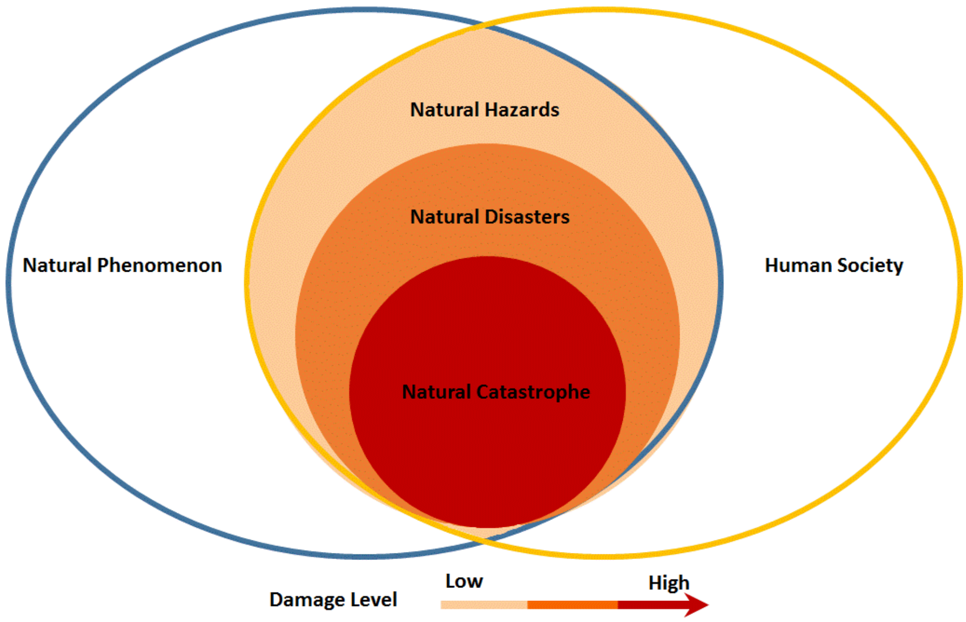


Figure 2.1. Conceptual linkages between natural disasters, hazards and catastrophe.

Conceptual linkages between natural disasters, hazards and catastrophe are shown in Figure 2.1, and it can be concluded that a natural hazard or a natural hazardous event is a natural phenomenon that leads to human suffering. When the natural hazard leads to unacceptable damage of property and affects thousands of people, it becomes a natural disaster (Leroy, 2006, Smith, 2003). If the disaster leads to destruction on a larger scale than the region has hitherto experienced, then it can be referred to as a natural catastrophe (OAS, 1990). The term selected depends on 'how much influence there is on the humans'. If the event occurs in a region that has no connection with people, it is not referred to as a natural hazard or a disaster (O'Keefe et al., 1976).

2.1.2. What are multiple natural disasters?

Multiple natural disasters are another type of natural event. Some multiple disasters consist of multiple independent natural disaster events, like the 'Double Typhoon Trouble' case, which refers to Typhoon Chan-hom and Severe Tropical Storm Linfa.

These two disasters involved large and powerful tropical cyclones that formed near the Pohnpei State (belonging to the Federated States of Micronesia) in June 25th 2015, and on the Philippine Sea on July 1st 2015, respectively. In early July 2015, both of them hit Taiwan and southern China and the direct economic loss to coastal cities in China exceeded 1.7 billion (Aon Benfield, 2015). In some multiple-disasters, the following event results from the first natural disaster, such as the storms and floods which occurred in UK in 2015. In early December 2015, Storm Desmond hit the UK bringing rainfall of 341.4mm over a 24-hour period. Severe flooding happened across Cumbria and the north of England, with more than 42,000 properties in Lancaster and 1,400 properties in Cumbria losing their power (BBC, 2015, Szönyi et al., 2016, WIKIPEDIA, 2016).

However, there is no certain terminology to describe such multiple disasters and in the most literature, the term multi-hazard is used to explain multiple hazards. The term multi-hazard was first mentioned in the United Nations Conferences on Environment & Development in Rio de Janerio, Brazil in 1992 (so-called Agenda 21 Conference) (UNEP, 1992). Without a clear definition, the Agenda 21 Conference called for 'complete multi-hazard research' in pre-disaster planning (Paragraph 7.61a). After a decade, the Johannesburg Plan used this term again and provided a complete multi-hazard measurement for disaster management and mitigation (UN, 2002). Later, disaster-related agencies, such as the International Decade of Natural Disaster Reduction (IDNDR) and the International Strategy for Disaster Reduction (ISDR), emphasized the importance for multi-hazard assessment in several of their reports. However, this term was mainly used in relevant approaches, as Hewitt and Burton (1971) referred to this term as the "all hazards at a place" approach, and Greiving (2006) described it as "hazards that are closely tied to certain areas that are especially prone to a particular hazard".

Thanks to the effort made by scholars such as Bell and Glade (2004) and (Kappes et al., 2012), the conceptual framework of 'multi-hazard' developed and gradually began concentrating on the features of the hazardous process, especially of occurrence time and place. Although there is no firm definition of multi-hazard, we can adopt the terminology from UNISDR (2017), in which multi-hazard is explained as "(1) the selection of multiple major hazards that the country faces, and (2) the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects". Hence, multiple disasters in this thesis can be defined as in the similar way, "(1) the selection of multiple natural disasters that the region faces, and (2) the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects".

Apart from 'multi-hazard', another term, 'compound events' has become more popular in climate science in recent years. Compound events can be regarded as a special type of climate extremes, while IPCC introduced the compound/multiple events as, "1) two or more extreme events occurring simultaneously or successively; 2) combinations of extreme events with underlying conditions that amplify the impact events, or 3) combinations of events that are not themselves extremes but lead to an extreme event or impact when combined. (Field et al., 2012)". Moftakhari et al. (2017) concluded it as "in which the simultaneous or sequential occurrence of extreme or nonextreme events may lead to an extreme event or impact". This term emphasized the combination impact of the natural hazard and flood in particular (Ikeuchi et al., 2017, Moftakhari et al., 2017, Wahl et al., 2015).

2.1.3. What is a flood?

Since the various speeds of occurrence of disasters influence human society in different ways, natural disasters are categorized into two types, rapid and slow onset disasters. The former, also named as sudden onset natural disaster, encompasses natural events that occur suddenly and strike rapidly with little warning (Nelson, 2014, OAS, 1990, Twigg, 2004). These events include: flash floods, lightening, and wildfires (which onset with virtually no warning); severe thunderstorms, hurricanes and river flooding (which can be projected several hours or days in advance); tsunamis and volcanoes (which erupt surprisingly but typically have hours, weeks or months of warning period). These kinds of disasters are difficult to predict precisely and lead to immediate short-term impacts on human society and the direct consequences of these disasters can be easily observed.

Slow onset or persistent natural disasters, refer to natural hazards that take far longer - several months or years - to develop. These events include heat wave, drought, desertification, air pollution, erosion, insect infestations, subsidence and disease epidemics (Nelson, 2014, OAS, 1990, Twigg, 2004). Compared with rapid onset events, slow onset natural disasters act slowly over a long period of months and years, and its impact becomes evident as time passes (Development Workshop, 2017).

Flooding is the core part of rapid/sudden natural disasters. It is a natural phenomenon caused when an overflow of water submerges dry land (Farooqm, 2018). In other words, it is “a covering by water of land not normally covered by water” (EU, 2007). Both environmental process and human activities can lead to flood disasters (FLOODsite, 2009; Parker, 2014, p.91-110). In mountain areas, the principal cause of flooding comes from the sudden melting of ice and snow. When precipitation from the water cycle is so large that it breaks the holding capacity of a region, the exceeded water can cover an enormous area and then it becomes a flooding disaster. In some cases of severe natural disasters, floods that are induced from the previous events often followed in its aftermath, such as storm-induced flooding. Slow moving storms can cause intense rainfall which then can lead to flooding further inland (Shepherd et al., 2013). One widely known event is the hurricane-induced flooding after Hurricane Katrina in the United States in 2005. This flooding accounted for nearly half of the total damage in this multi-hazard case (Boettke et al., 2007). Meanwhile, human action is another major reason for flooding, such as flooding resulting from a damaged dam in a coastal area (Parker, 2014, p.163-172). Depending on the physical features of floods, flooding disasters can be divided into several types (FLOODsite, 2009). For coastal and river floods, the 'water in flooding' is different depending on whether it is from the sea or river. Flash flooding is mainly caused by heavy rainfall and refers to flowing water that suddenly runs at fast speed, submerging a specific area; ponding or pluvial flooding is another type of flooding that is caused by rain water, and the flooding occurs in relatively flat areas. It is worth mentioning that, during recent years, attention has increasingly been paid to urban flooding, due to the high speed of urbanization (Hallegatte et al., 2013, Hammond et al., 2015). Urban flooding is a special flooding type that results from flash, coastal or river floods and occurs in urban areas, generally due to lack of urban drainage. Groundwater flooding, is another flooding type that occurs in many regions and the United Kingdom in particular Such floods occur in case of sub-surface water emerges from the ground, because of heavy rainfall or high river levels (SF, 2018). However, groundwater flood rarely gets less attention when compared with other flooding types. Currently, since it has been recognized as a significant source for the UK flooding, many local flood authorities in the UK has undertaken research for groundwater flooding, such as the British Geological Survey (BGS, 2017, GOV.UK, 2014). Regardless of the type, floods have become the most threatening natural disaster for human society (Kubal et al., 2009, Mens et al., 2011, Jongman et al., 2014, Winsemius et al., 2016).Storm-induced floods are frequently experienced by coastal regions around the world.

With respect to storms, it shares nearly 28% of occurrences of natural disasters during the period of 1995-2015 (CRED, 2015b) and is the second most frequent hazard in the whole natural disaster system. A storm is described as "any disturbed state of an environment or in an astronomical body's atmosphere especially affecting its surface, and strongly implying severe weather" (SSA, 2018). Phenomena like strong wind, hail, tornadoes, thunder, lightning, and heavy precipitation, generally accompany storms. When several tropical storms reach a populated area with heavy rain and strong winds, this can lead to disastrous consequences in the affected regions. A storm system can cause familiar natural disasters such as hurricanes, cyclones or typhoons (NOS, 2018).

2.2. Consequences of Floods: Direct and Indirect Effects on Human Society

Flood disasters act on human society with immediate effect and with enormous destructive consequences. EM-DAT records the frequency and the number of affected countries experiencing floods as higher than any other natural disaster type. Since the twentieth century, flood-related disasters have accounted for 51% of the total affected people and 22% of the total mortality, and have created over 24% of the total of disaster-induced economical damages (Aon Benfield, 2017b). The indirect effects of flood consequences hide behind the direct influence and economic impact is generally responsible for the largest loss. As an invisible influence, indirect economic impact occurs generally in the post-disaster period along with the reconstruction process. However, such post-disaster impacts still remain a mystery since the practice data is not available due to the complexity of the situation. Unless the flood-induced direct/indirect consequences are realised, and the post-disaster economic system assessed, a full picture of the indirect economic impacts caused by flooding cannot be presented.

2.2.1. Direct Impacts: First-hand and Apparent Consequences

In general, weather-related disasters hit a region causing several direct impacts on the human population and physical assets (as shown in Figure 2.2). It is easily understood that an intense storm surge and related wave action, along with the shock of tropical cyclones, or the strong water flow from flooding, can lead to destruction of fixed assets, crops, raw materials, basic infrastructure and other physical capital (Shepherd et al., 2013, Noy and IV, 2016). In the United States, historic flooding has damaged more than 182,000 homes and businesses in Texas alone, with major or minor economic loss. In 2017, flooding in Peru led to over USD 3.0 billion in damages and in China, flooding has caused a USD 7.5 billion loss (Aon Benfield, 2017b). The sectoral analysis demonstrates that residential damage accounts for over half of the total economic loss, followed by commercial and industrial damage (Alfieri et al., 2017).

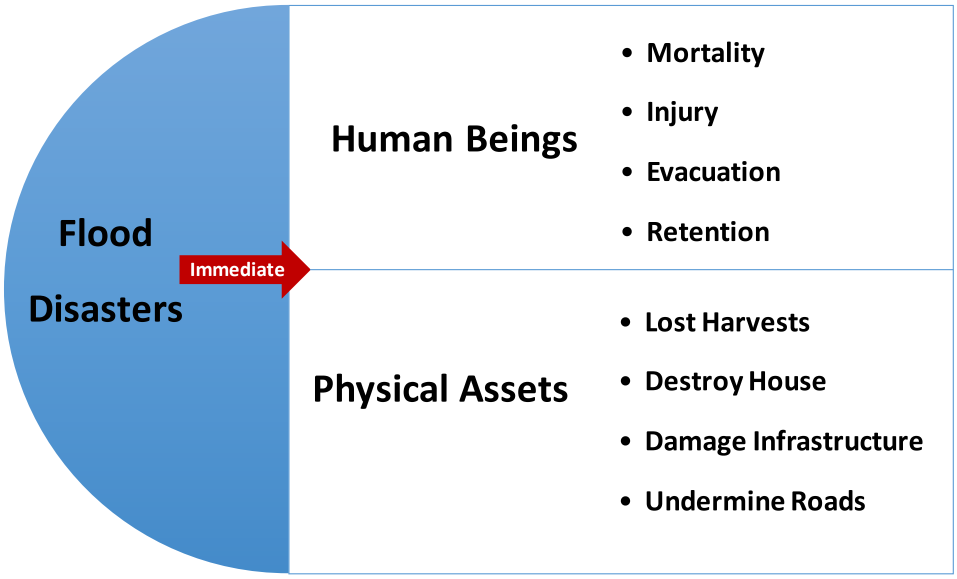


Figure 2.2. Direct influences caused by flood disasters on human society.

As the most vital element of human society, millions of people, particularly people killed or injured during the disaster process, suffer immediate and irreversible consequences of natural disasters. Since 1995, total fatalities from natural disasters reached 1.4 million, of which 11.2% resulted from flood disasters and storms, accounting for 242,000 fatalities (CRED, 2015b, CRED, 2016). When reviewing historical floods, Doocy et al. (2013) conclude that the influence that floods had on human populations varied greatly over the years and were primarily centered around large-scale flood events. Globally, flood-related events resulted in 8.2% of disaster-induced death during the decade from 2006 to 2015, a reduction from 14.4% between

1996 and 2005. Flooding affected 2.3 billion people from 1996 to 2015, excluding the death, but including those affected by evacuation and retention. This represents about 56% of the total affected population, while another 16%, (over 660 million) were affected by storms (CRED, 2015b).

Geographically, the less developed and higher populated countries experienced the majority of flood-related risk. At the regional level, Asia experienced more floods and mortality than any other country. For example, over 2,100 people in Pakistan and 1,900 people in China died due to flooding disasters in 2010, and three years later, the 2013 Indian floods killed more than 6,500 people. Other regions such as Africa, Europe and the Eastern Mediterranean together accounted for 8% of the flood fatalities and 4% of the flood-affected population (Doocy et al., 2013). Meanwhile, Asia and Africa together experienced 73% of the total economic loss while all others shared the remaining 27% (Alfieri et al., 2017). With the contributions of climate change, the majority of regions are predicted to experience more serious flood impacts on population and physical damage. Based on the IPCC climate-related scenarios, Alfieri et al. (2017) have projected future maps of average potential changes in the amount of river flood-induced population affected and the expected damage for each country in the world at specific warming levels, compared with pre-industrial levels (Figure 2.3). With the temperature increasing by 1.5°C, 2°C and 4°C, Asia, the United States and Europe are expected to face increasing impacts by river floods, with only Latvia showing significant negative changes in all scenarios.

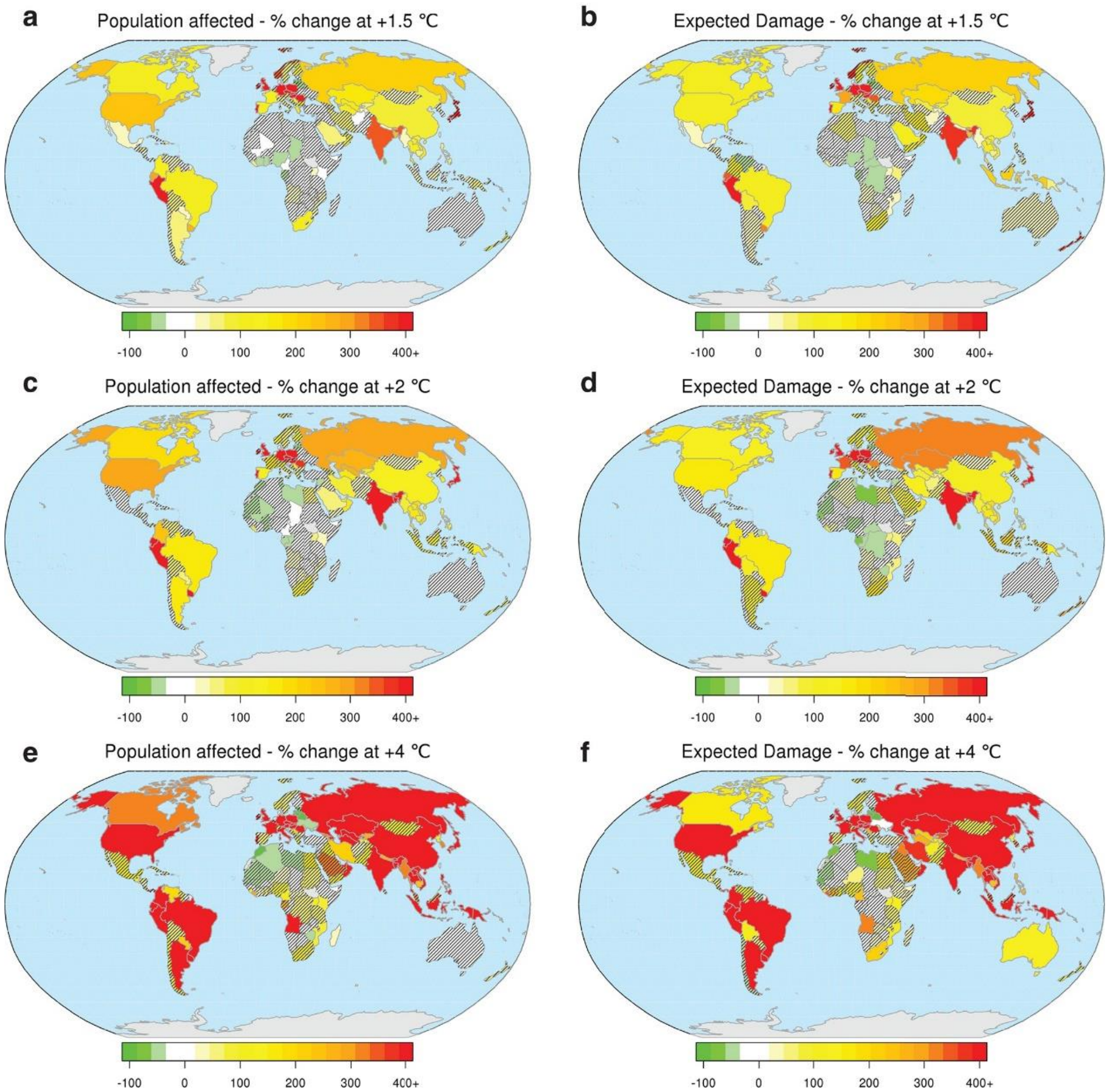


Figure 2.3. Average changes in affected population and expected damage per country by river floods under specific warming levels (1.5°C, 2°C and 4°C) as the baseline of pre-industrial level. Source: Alfieri et al. (2017).

2.2.2. Indirect Impacts: Second-hand and Invisible Consequences

Indirect consequences of natural disasters result from direct impact to damaged properties; these consequences include emergency cost, decreased demand or output, business interruptions, consequences for economic growth, health impact, disruptions on social-ecological system, and influence on poverty, security, stability and sustainability (Noy and IV, 2016, Hallegatte, 2014, Okuyama and Santos, 2014).

When considering the indirect loss, indirect consequences generally occur at various levels. At an individual level, damaged infrastructure and commercial structures may lead to changes in sales, wages or profits in the affected region; at the business level, both regional input and output may be influenced due to disrupted transactions and flows; more widely, the impact may extend to other regions or economic systems that the disaster does not hit immediately. Regardless of impact level, economic activities account for the most indirect loss from a given natural disaster (NRC, 1999).

One point should be emphasized here: immediate/direct and secondary/indirect impact do not respectively equal the short-term or long-term impact in hazard research, particularly in sudden onset natural disasters. In general, whether the region is directly in touch with the natural disaster determines the type of impact - direct or indirect. However, the classification of short-term and long-term impact is principally determined by the time period suffered by a region. If the disaster loss accounts for a few months up to several years, it pertains to a short-term impact; when it takes at least three to five years, or even more, to cope with the economic loss, it pertains to long-term impact (Noy and IV, 2016). This means that, for rapid natural disasters, the direct impact is short-term, whereas the indirect consequences can involve both short-term and long-term impacts (NRC, 1999) (P.37). Since this thesis concentrates on assessing the indirect economic impacts at a regional level, the content below mainly refers to the regional indirect economic impact resulting from flood disasters.

Albala-Bertrand (1993, p.104) expressed the indirect effect of natural disasters as “more a possibility than a reality”. In an economy it is difficult to establish accurate indirect loss, due to limited available data and the complexity of the economic system. Thus, indicators such as national income accounts (GDP), tax revenue, payments balance and regional production are commonly used to measure loss. As various indicators are estimated by different approaches, the consequences of a given disaster may differ. No matter what indicator is adopted, several studies provide the evidence that indirect economic assessment is necessary because the percentages of indirect impacts sometimes account for more than the direct impact (Rasmussen, 2004). By collecting the statistical data obtained from post-disaster data surveys, Charvériat (2000) found that natural disasters led to an average 1.7% reduction of the same-year GDP in 28 cases; but from the analysis by Caselli and Malhotra (2004), the results showed that a natural disaster has no significant influence on the local economic growth path. Carrera et al. (2015) combined a spatial analysis that linked direct damage to physical stock with a computable general equilibrium (CGE) model to test the direct and indirect economic impacts of the 2000 Po river flood that occurred in Northern Italy. Their results showed that the direct economic impacts that depended on water-depth were estimated in the range of 3.3 to 8.8 billion Euro (at year 2000 values), while the indirect economic loss limited by various substitution and disruption duration conditions, were 0.64 to 1.95 billion Euro. In this case, the approximated indirect impact equals 19% to 22% of the direct economic impact. However, various factors determine the role of the indirect economic impact, such as the scale of specific natural disasters, economic conditions or the development level of the affected region and the resilience of the economy. As Cochrane (2004, pp 42-43) said, "Indirect loss […] is less sensitive to economic structure (manufacturing dominated or service dominated economy) than to damage pattern, degree of integration (size), pre-existing conditions, and who is financing the recovery". Likewise, Cavallo et al. (2013) concluded that only under the condition that the natural disaster led to a radical political revolution, can the disaster affect economic growth and create large indirect economic consequences.

Results from other quantified studies also illustrate that natural disasters influence economic activities through indirect means which can lead to a great number of losses (Hallegatte et al., 2007). As the production and consumer sectors determine the structure of an economy, any changes to these sectors will influence the economic balance and lead to indirect impacts. For example, with respect to the labour force, either employment or workplaces affected by natural disasters will result in decreased production, which will then result in an indirect economic loss (in den Bäumen et al., 2015). Koks et al. (2015b) estimate that if the labour recovery period after the flooding is as long as two years, the indirect losses will triple when compared with the reference situation. Other factors, like import constrained by damaged transportation and alternative consumer behavior in the aftermath, can also generate indirect costs to the economic system (Baghersad and Zobel, 2015, Steenge and Bočkarjova, 2007).

2.2.3. Post-flood Economic Recovery: A Hidden and Mysterious Process

Increasingly, scientific research shows that climate change will increase the frequency of floods in the future (CRED, 2015a, Arnbjerg-Nielsen, 2014). More regions, and cities in particular, will be at risk of exposure to human loss and economic loss through natural disasters (Eakin et al., 2017). Records show that in 2016, economic loss of about 150 billion GBP and 8,733 fatalities were caused by natural disasters around the world. This included 44 billion GBP and 4,731 deaths resulting from flooding events (Aon Benfield, 2017a). The shocks of sudden-onset natural disasters not only result in human mortality and morbidity, and destroyed physical capital (such as damaged infrastructure and buildings), but also interrupt economic activities. This can then lead to a further economic cost that people would not see directly, especially as the majority of economic activities around the world are highly concentrated in cities. Hence, comprehensive analysis of economic impact by floods on industrial and economic systems is an urgent and essential part of urban recovery and sustainable development (Kubal et al., 2009, Chen et al., 2009, Haddad and Teixeira, 2015, Rose and Lim, 2002). As Ahrens and Rudolph (2006) have stated, “Disasters can essentially be viewed as a function of the risk process, i.e. they result from a combination of hazard, conditions of vulnerability and insufficient capacity or measures to reduce the negative consequences of risk”. Understanding the resilience of an economy is the first step to assessing post-flood economic conditions because it illustrates the immediate bearing on the total damage that is sustained by an economy (Klein et al., 2003, Cutter et al., 2008, Espinoza et al., 2016).

2.2.3.1 Resilience of Economic System

Research associated with the economic impact assessment of natural disasters has tended to concentrate on larger units of analysis rather than individual enterprises and firms, such as in regional and community economies (Tierney, 2007)(p.275). When considering the characteristics of the economic system before and after a natural hazard, resilience, vulnerability and adaptive capacity are the three terms commonly used in the relevant literature. A number of studies of social-economic system analysis focus on identifying the conceptual framework of these terminologies and developing approaches for their assessment (Burton, 2015, Meerow et al., 2016). However, there is no single accepted description of resilience or vulnerability of an economic system (Klein et al., 2003).

The term ‘resilience’ was first used by Holling (1973) to illustrate a “measure of the persistence of system and their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables”. Following the work by Adger et al. (2005), Folke (2006) and others, Cutter et al. (2008) concluded that resilience was the capacity of a system to assimilate disturbance and rearrange into a completely functioning system that equals or betters the pre-disaster level after learning and adaptation. Thus, for natural disasters, resilience particularly shows the ability of an economy to survive with the lowest damage and impact (Berke and Campanella, 2006).

A key part of resilience, proposed by scholars from environmental and climate change, is adaptive capacity. This can be defined as the ability of a system to respond to a disaster by adapting to change and mitigating the influences (Burton et al., 2002, Cutter et al., 2008, Daramola et al., 2016). Another term, ‘vulnerability’, indicates the physical characteristics or qualities of a given system when facing shocks. Generally it refers to a system's exposure and sensitivity to disaster-induced harm (Cutter, 1996). In other words, it demonstrates who and what will be damaged and the degree of severity that they suffer due to a specific natural hazard (Siagian et al., 2014, Koks et al., 2015c). Both resilience and vulnerability are dynamic processes, but resilience can reflect both the ability of a system to recover from a disaster and to mitigate disaster influences through various adaption behaviours. Hence, resilience can be regarded as an outcome in the former condition and serves as a process in the latter situation (Cutter and Finch, 2008). As a dynamic process, resilience of an economy to a natural disaster implies minimal economic loss during the recovery process with the appropriate approach. The better the mitigation techniques adopted, the higher the resilience and the lower the sensitivity of an economy to hazards is (Bruneau et al., 2003).

2.2.3.2 Post-flood Recovery at Economic Level

Since mitigation of a disaster-induced impact is the core part in hazards-related resilience research, the post-disaster recovery process becomes the centre of resilience assessment (Noy, 2009, Cutter et al., 2008). The destination of recovery includes two types, one is back to the pre-disaster economic state and the other is an advanced state, after learning and adaptation (Folke, 2006). If there is no other notification, the default destination for the disaster-induced recovery process is the first type, in which the recovery starts from the natural disaster occurrence and stops when economic transaction returns to the pre-disaster state. A variety of studies provide evidence that, either from a short-term or long-term view, various regions reveal a diversity of post-disaster recoveries in the aftermath of natural disasters. A Report by the International Monetary Fund (IMF) states, "adverse external shocks have a significant negative impact on short- and medium-run growth through their effect on aggregate demand, external balances, and the government's fiscal position" (Dabla-Norris and Gündüz, 2014). Both internal and external factors can affect a region's ability to recover in the aftermath. As demonstrated by Asgary et al. (2012), such internal factors mainly include the disaster type and size, risk mitigation and industrial continuity plan, financial capacity, industry ties, and the scale of direct and indirect damage. External factors indicate the factors that are out of the control of business, such as community disruption, and available support from social institutions.

Most studies show that regions (including household, subnational and national levels) with a high socio-economic structure suffer less economic impacts and are highly resilient to natural disasters. Noy (2009) analysed the linkages between GDP growth, affected population and the direct cost of natural disasters through EM-DATA statistical data for the period 1970 to 2003, for all recorded countries. Noy (2009) found that, after the same scale of natural disasters, developing countries and smaller economies suffered much larger output declines when compared with developed countries or bigger economies. Meanwhile, countries with a higher rate of salary per person, a greater degree of trade transparency and higher literacy rates, were better able to respond to the disaster shock and prevent further impact. Heger et al. (2008) concluded that the "diversification of the economy can help mitigate the effects of natural disasters", and a higher independency to export and import can result in larger damages after natural disasters. There is no clear evidence to show the connections between capital damage and aftermath output changes. Noy (2009) and Cuaresma et al. (2008) propose the view that higher capital damage caused by natural disasters create a higher decreased output in developing regions and the opposite is experienced among more developed countries. Mechler (2009) adopted a cross-country analysis and illustrated that only in low-income countries, capital loss adversely influenced consumption; among other regions, the damage to assets did not result in major changes in consumption.

External assistance, such as import production and financial aid, are helpful to reduce adverse economic consequences. The Vietnam-based disaster case, studied by Noy and Vu (2010), concluded that, thanks to sufficient funds for reconstruction supported by the central government, the affected region experienced a short-run growth spurt after the disaster. Hochrainer (2009) posits that greater inflows of remittances and external aid are able to reduce adverse economic impact, and then direct loss becomes more critical. In addition, the scale of the natural disaster determines the level of economic consequence (Cunado and Ferreira, 2014, Hallegatte and Przyluski, 2010). Hochrainer (2009) argues that natural disasters generally lead to negative consequences in a medium-term analysis (up to 5 years) and concludes that "although the negative effects may be small, they can become more pronounced depending mainly on the size of the shock". Fomby et al. (2013) find that moderate floods have a positive effect while severe floods have a negative effect on economic growth (Cunado and Ferreira, 2014).

In principle, the main characteristics of regional and economic recovery correspond significantly to the regional development level, damage degree of industries, external assistance (e.g. import and financial aid) and other factors such as insurance and reconstruction speed (Poontirakul et al., 2016, Von Peter et al., 2012). For example, Deraniyagala (2016) proposes that a lower speed of reconstruction may extend the economic consequence at both household and regional levels. However, in studies about post-flood economic impact and recovery analysis, less attention was paid to another common phenomenon, 'delayed recovery'. It often exists in many real flood cases and refers to the situation after the natural disaster shock, when elements of an economy, such as labour and individual sectors, are not able to recover immediately. For instance, Hurricane Katrina, a natural disaster which hit the United States in 29 August 2005, and caused over 81 billion USD of property damage and the displacement of more than one million people, was followed by massive flooding in New Orleans, which caused this city to essentially be 'closed' for nearly a month. Sydnor et al. (2017) underlined that if a business is closed immediately for a long time after a natural disaster, the probability of customer and supplier attrition will become higher, and recovery and continued operation of the business will be less likely.

Whether ‘delayed recovery’ occurs for a certain natural disaster depends upon a variety of factors. At the small business level, the owners may decide to rebuild or repair structures some days after the disaster, due to a lack of adequate insurance or the fact that they primarily focused on their residence rather than their business.

Regarding the economic level, the following two main reasons contribute the most to delayed recovery. One is post-flood governance. Ahrens and Rudolph (2006) indicate that the quality of governance directly determines the recovery quality in the aftermath by strengthening or weakening the regional capabilities to natural disaster. Pathak and Ahmad (2016) emphasize the crucial role of governance as “the governing of several factors such as disaster management, aid and assistance programmes form the foundation for faster disaster recovery and enables the economy to bounce back to normalcy”. In the case of Hurricane Katrina, Corey and Deitch (2011) point out that, after Katrina, inappropriate and uncoordinated governance at all levels - local, state and federal - made business recovery more difficult. As cash flow problems were faced by most businesses after Katrina (Runyan, 2006), external aid for these sectors was expected to overcome the shortfall in funds. However, relevant departments failed to supply direct financial aid efficiently within the post-Katrina economic recovery and led to a delayed recovery for many sectors.

The other factor is related to industrial ties. Tierney (1995) researched the case of the 1993 Midwest floods in which floods struck the United States in the summer of 1993 and resulted in nearly 20 billion USD of direct damage. However, utility disruption contributed more to business closures than direct damage. In Des Moines, the state capital of Iowa, only 15% of businesses in this city were extensively damaged by this flooding and yet the percentage of this sector that were forced to close because of poverty in water, sewer, electricity or phone services was estimated as high as 42%. Clearly, inter-linkages among industries can make a sector that is unharmed by a flood become a ‘damaged sector’ and this will then impact negatively on recovery. Corey and Deitch (2011) reported that as power, clean water and natural gas were unavailable for extended periods, most businesses had to close for 2 to 8 weeks. Six months after Hurricane Katrina, approximately 25% of the population was still outside the New Orleans area. Moreover, they concluded that because “basic ‘lifeline’ services were non-functional for varying lengths of time across the region”, industrial recovery was severely hampered in this region.

Transport infrastructure is also an important sector for recovery. As Luther (2006) reports, the amount of Katrina-related debris that was created was the greatest in the United States history; this debris blocked roads and produced constraints on the supply of lifeline productions, and limited the recovery of the business structure, creating delayed recovery for some sectors in the aftermath of Katrina (Sydnor et al., 2017).

2.2.3.3 Post-flood Recovery at Business Level

One extremely important factor in post-disaster recovery is the ability of the business and other sectors to survive and thrive after a widespread natural disaster (Asgary et al., 2012). As the foundation of local and regional economies, destruction of business and other sectors results in greater challenges on various levels, including households and communities, such as the loss of jobs and a negative effect on incomes. Von Neumann (1971), who addressed the particular question of ‘how to grow the economy’, had a suggestion that so-called proportional or balanced growth is provided within economies for supporting a circular flow. Such proportional growth means that all sectors possess the same growth rate. The fact that a proportional rationing scheme is manipulatable, because one can artificially increase his/her demand to get more, will be disregarded in the following. However, there is no empirical evidence to illustrate how businesses recover in the aftermath and there is a lack of research to show the recovery path of each sector in a given economic system. As Tierney (2007) suggests, topics related to business vulnerability, measurements of loss-reduction that are employed by business, and disaster impact on sectors and business recovery, have been little studied or understood .

The United States is the region in which the most studies about impact analysis on business continuity and post-flood recovery are focused (Corey and Deitch, 2011, Asgary et al., 2012, Dietch and Corey, 2011). Rose et al. (1997) illustrated that the disruption of the electricity service alone, after a major earthquake that occurred in the Memphis area, resulted in an estimated economic loss within the recovery period of as much as 7% of regional GDP. Webb et al. (2002) stated that, after Hurricane Andrew in Florida in the United States, wholesale/retail-related sectors were less likely to recover than any other sectors. Corey and Deitch (2011) investigated the factors that impacted on the recovery and short-term performance of organizations during the period of the 6 to 8 months after Katrina. They found that the most vulnerable industries were associated with the wholesale/retail sectors and that construction-related sectors had higher levels of organizational performance within post-Katrina. In addition, they suggested that the businesses who purchased adequate insurance pre-disaster received more resources for their recovery from the storm than other sectors without any insurance.

Regarding population-related variables (customer loss or staff loss), the analysis of Corey and Deitch (2011) showed that three years after Katrina, population issues were still affecting business recovery and this negative impact was expected to persist long after all the physical damage had been restored. Similarly, Stevenson et al. (2014) and Sydnor et al. (2017) noted that lack of staff was one of the challenges that was experienced by many sectors during an aftermath recovery period.

2.3. Measurements of Flood-induced Economic Impacts: Manifold Diversity

Several efforts have been made to measure disaster/flood-induced indirect economic impacts using diverse methodologies and indicators. The common approaches can be divided into two types, primary data collection and relevant models. Although primary data collection is a way of obtaining reliable data, this approach is sometimes difficult to carry out due to the great workload and varying quality of the data. For direct economic effect assessment, empirical modelling (constructed on empirical observations), are developed to a more mature degree, such as water-depth models for flood direct damage calculation. Meanwhile, the indirect economic impact analysis framework is still in an early development stage, and the economic-based model seems to be more effective than econometric models, since the former can take more factors into account, particularly Input-Output models.

2.3.1. Direct Assessment Tools

The direct economic impact of a natural disaster to human society, also known as immediate economic consequence, is defined as "the monetary value of total or partial destruction of physical assets existing in the affected area" (UNISDR, 2017). Put simply, direct economic loss is equivalent to the cost of physical capital/stock caused by natural disasters (Rose and Lim 2002). Measurement of such an impact for a given disaster is often organized by the relevant department or insurance companies. The direct economic loss from the event will then be made known to the public. For official agencies, especially the government in China, the commonly used method for loss evaluation is through primary data collection from post-disaster questionnaires, surveys and interviews (NRC, 1999). Although the results are sensitive to the inconsistencies of data sources, it is the most suitable approach to obtaining the practical data. For instance, after comparing impacts and frequencies of a cross-country sample during 1970 to 2002 that was based on the EM-DAT database of natural disasters, Rasmussen (2004) analysed the spatial characteristics of natural disaster cost in the Eastern Caribbean Currency Union and observed that the aftermath of natural disasters have negative effects on economic output.

Apart from the collection of primary data, another main approach applied to the estimation of short-term economic loss is through empirical loss estimation models, which refers to the mathematical models based on damage or loss functions (Rose and Lim, 2002, Merz et al., 2004). Pertaining to flooding disasters, the principle theory of the damage/loss function is that the direct damage for a specific type of land-use or buildings largely corresponds to the particular features of the flood, such as water-depth, inundation duration, flow velocity, sediment concentration, availability of flooding warning and other external responses to floods (Smith, 1994, Penning-Rowsell and Fordham, 1994). Differently from flooding, the direct capital damage of storms to the specific use of buildings or land-use are mainly determined by the physical features of storms, such as maximum wind speed, storm duration and size, wind direction, storm surge and precipitation, and local exposure level (Zhai and Jiang, 2014). However, regardless of the type of rapid onset natural disaster, there is no comprehensive approach that considers all the factors in a natural hazard, due to poor data and undeveloped techniques (Merz et al., 2004).

The combination of primary data collection and mathematical models is an effective way to estimate the direct economic damage on tangible assets in the aftermath, when the practical data is not available. With improvement of observation tools, the results of disaster-induced direct economic impacts will become more reliable as we can access more precise data and information.

Among all the models, depth-damage function is the most common methodology for assessing direct tangible damage resulting from floods, since the risk for each building type or land-use class is highly reliant on inundation depths, and potential loss of total physical damage can be calculated by depth-damage curves (Koks et al., 2015a, Jonkman et al., 2008, Smith, 1994). This methodology dates back 40 years, and is based on practical observation. Grigg and Helweg (1975) proposed the view that the depth-damage curves of buildings with similar structure or type show similar trends no matter what the actual value is. The economic loss for a certain building or land-use type resulting from various floods can be modelled using actual data from aftermath-damage data collection, combined with synthetic data used to estimate the damage of a specific flooding situation through 'what-if analyses' (Merz et al., 2004). Based on this theory, it seems that the Blue Manual of Penning-Rowsell and Chatterton (1977) provides the most comprehensive approach in the current stage because it includes stage-damage curves for commercial property and residential housing in the UK region. A stage-damage curve indicates the damage fraction of the maximum value at risk for a particular land-use category at a particular inundation depth. In recent years, a growing number of studies have estimated the direct damage loss of a certain flood by integrating depth-damage functions with spatial information on building or land-use types, leading to a more accurate and reliable result. For example, there is a more advanced model ('HAZUS-MH Model'), offered by the Federal Emergency Management Agency (FEMA), from the United States, to evaluate the economic risk induced by earthquake, winds and floods. With the help of ArcGIS from the ESRI Company and the Digital Elevation Model (DEM) from USGS National Elevation Dataset Website, the software HAZUS-MH Flood Model is able to analyse structural damage to infrastructure and buildings by considering the spatial characteristic of water-depth and flood velocity in a given area. Although this model has been continuously updated since 1997, the significant limitation pertains to the specific study area. It can only be applied to regions in the United States as the default profile and basic input (such as building distribution maps) are based on the conditions in the United States (Scawthorn et al., 2006a, Scawthorn et al., 2006b). In addition to the US-based HAZUS-MH model, other models like web-based Multi-Coloured Manual (MCM) (Penning-Rowsell et al., 2014) and Dutch-based HIS-SSM (Koks et al., 2012) are also able to quantify the physical damage cost of sudden-onset natural disasters. Both of them are built upon depth- and stage- damage curves, but the former focuses on the UK region while the latter is suitable for the Netherlands. The variation of region-based studies by de Moel et al. (2014) help us further understand how to utilize these flood damage models and gain more effective and efficient results when the research area is beyond the relevant models' regions, in particular when estimating the risk value for a certain land-use type.

Current empirical hurricane/cyclone economic loss models are based primarily on the damage-intensity function due to the fact that it has been examined extensively (Nordhaus, 2010, Zhai and Jiang, 2014). Damage–intensity shows the relationship between hurricane normalized damage value and maximum wind speed. Nordhaus (2010) gathered information about storm features and relevant economic loss for 233 hurricane events in the United States area during the period of 1900 to 2008 and concluded that 'damages appear to rise with the ninth power of maximum wind speed'. HAZUS-MH Hurricane Model is another type of HAZUS-MH model that has been developed by FEMA to compute building damage caused by storm-related disasters. This model is based on the hurricane hazard model that includes the database of historical storms occurring along the Atlantic Basin from 1886 to 2001. By comparing storm factors such as wind speed, storm intensification, radius to maximum winds to central pressure and latitude, HAZUS-MH Hurricane Model is able to provide damage fractions and risk values for various types of buildings and land-use after storm disasters in the US regions (Vickery et al., 2006a, Vickery et al., 2000b, Vickery et al., 2000a, Vickery et al., 2006b).

2.3.2. Indirect Assessment Approaches

Immediate damage induced by natural disasters leads to an aftermath of economic consequences in the affected region, since sudden-onset natural disasters disrupt economic activities and break the balance among suppliers and consumers after the event. It may require a period of weeks, months or years for the economic system to return to pre-disaster level. During this process, 'a decline in economic value added as a consequence of direct economic loss and/or human and environmental impacts' (UNISDR, 2017) is described as the term of indirect economic impact, or the secondary economic impact. Currently, there are three types of quantitative approaches used when quantifying and assessing the indirect economic impacts of natural disasters.

2.3.2.1 Post-disaster Economic Survey

The first type of quantitative approach is a post-disaster economic survey (Baade et al., 2007). It is based on receiving the exact data on real disaster events, such as data on reconstruction of damaged buildings and period of evacuation shelters. Kroll et al. (1991) evaluated the economic impacts of the 1989 Loma Prieta earthquake in California by collecting published economic data. Through the survey of small businesses at industrial and city levels, they found that the centre of the earthquake and the main economic activities were out of the populous region. Additionally, the strong communications and utilities system and alternative transportation system, are the main reasons why the affected regions recovered quickly from the earthquake. Based on the observed data of GDP and outcome, Cavallo et al. (2013) adopted comparative case studies, which are more general than the fixed-effects model, to estimate the average direct and indirect impacts of larger disasters on real GDP per capital. They focused on the countries that experienced severe disasters from 1970 to 2000 (where the related data is available) and concluded that natural disasters do not influence subsequent economic growth significantly. This means that only destructive disasters affect economic growth and general hazards have less impact on incomes or employment in the long-term view. Molinari et al. (2014) proposed a new procedure for flood-damage data collection in residential and commercial sectors at the local level, since the current tools and procedures for data gathering were not sufficient to define or validate the damage curves, due to the poor, fragmented and inconsistent information. They emphasised that in the surveys of disaster-induced indirect damage, questions of lost clients, lost working days and the consequences of labour should be included.

2.3.2.2 Econometric Models

The second type of quantitative approach is the econometric model, which primarily refers to statistical models used in econometrics and specifies the statistical linkages of various economic quantities in the aftermath of natural disasters (Noy and duPont IV, 2016, Husby et al., 2014, Cerra and Saxena, 2008, Barro, 1991). The standard theory of this methodology was first proposed by Solow (1956), who proposed that countries should rely on a steady-stage growth path. Thus, the Solow Model suggests that natural disaster will not result in a long-term impact on the economic system due to the fact that the interrupted economy will finally return to its pre-shock growth path. The concept of the Solow Model is not suitable for real cases due to the fact that disaster-related factors (like human capital or the quality of post-disaster governance) can also affect long-term growth. However, it is still regarded as a reasonable theoretical basis (statistical-econometric techniques) to test how the influenced area will return to its pre-disaster trend (Noy and duPont IV, 2016) with the contributions of relevant models (Husby et al., 2014, Deryugina et al., 2014, Barro, 1991), such as the macroeconomic model developed by Albala-Bertrand (1993). This model can be employed when examining the relationship between a sudden-onset natural disaster and its potential effects by considering the growth rate of output. Albala-Bertrand (1993) applied it to six disaster situations in Latin America and indicated that capital loss did not significantly affect the economy and very moderate response expenditure may be sufficient to prevent the fall of the growth rate of output. With a panel vector auto-regression (VAR) model, Raddatz (2007) investigated the dynamic consequences of external shocks (including natural disasters) on the volatility of output in a sample of 40 low-income countries over the period 1965 to 1997. They gathered the disaster data from the EM-DAT database and illustrated that the external shocks led to modest effects on per capital GDP and output volatility was heavily dependent on internal causes. However, for climate-induced disasters, it is important to consider the disaster-induced influence on the economy, since it can result in a 2% decrease in real annual per capital GDP in the aftermath. Another widely cited methodology is short-run macroeconomic response built by Noy (2009). By considering natural disaster-induced mortality, affected population and direct economic cost, the authors created a regression of the annual GDP growth rate that is associated with disaster influence and other control variables to reveal the aftermath impacts of natural disasters.

2.3.2.3 Economic-based Models

Numerous multidiscipline methodologies based on economic models have been employed to describe the consequences of natural hazards and the primary methods include Input-Output (IO) model, computable general equilibrium (CGE) mode, and social accounting matrix (SAM).

(1) Input-Output Approach

The IO approach has been the methodology most widely employed for disaster risk analysis (Miller and Blair, 2009). The IO table is the foundation of the IO model since it is able to capture the inter-linkages among industries and present the balance between supply side and consumption side for a given region or economic system. Due to its being focused on the supply-side of the economy, the IO model is able to reveal the changes in supply of outputs when the input constraints and supply bottleneck occurs. Hence, disaster-induced decreased production can be measured and the indirect economic impact can be assessed (Oosterhaven, 1988). On the basis of IO theory, HAZUS, an indirect damage estimation tool was developed by the United States Federal Emergency Management Agency and the National Institute of Building

Sciences and later developed into a software programme (Scawthorn et al., 2006a). The Indirect Economic Loss Model component of HAZUS uses the post-disaster surviving capacity in terms of surviving production as a starting point for recalculating inter-industry supplies and demands (Scawthorn et al., 2006b, Remo et al., 2016), but the HAZUS only suitable for the area of the United States. The application of the IO approach to disasters, and natural disasters in particular, can be traced to the period of the Second World War (Rose and Guha, 2004, Okuyama, 2007). Other early studies based on the IO model, to assess the natural hazards impacts, come from scholars like Cochrane (1974, 1997) who offered a brief analysis of relationships between direct and indirect losses caused by natural disasters through an inter-industry model. Based on the study of the economic consequence assessment of an earthquake that occurred in the American Midwest, Cochrane (1997) made a suggestion based on the application of the inter-industry model and proved that such a method can be used as a measurement for natural disaster-induced indirect economic loss. More recently, work by Steenge and Bočkarjova (2007), Hallegatte (2008) and Li et al. (2013), Koks et al. (2015a) and Mendoza-Tinoco et al. (2017) showed that the IO model is the ideal choice for economic impact assessment, especially on indirect economic loss estimation.

Although the IO model is not particularly flexible, with some adaptive formulation it is able to reach a high analytical specificity and allows for dynamic simulation (Miller and Blair, 2009, Hallegatte, 2008, Okuyama, 2008, Santos and Haimes, 2004). Steenge and Bočkarjova (2007) offered an imbalance growth model based on the IO framework to estimate the economic consequences of a major catastrophe, but this model is not able to show the dynamic changes in the post-disaster economic recovery. Hallegatte (2008) proposed a new regional adaptive IO model to assess the economic loss of natural disaster at the regional level. However, his model exclusively considered the production capacity and adaptive behaviour after the disaster, while destruction of housing and labour constraints were neglected. Li et al. (2013) constructed a monthly IO model based on dynamic inequalities to assess an imbalanced economic recovery in a post-disaster period. A series of dynamic inequalities was developed as their theoretical basis. This methodology is better suited to analysing changes in a regional economy and assessing regional economic losses, vulnerability, and resilience during the recovery period after a disaster. However, this model was only applied to a hypothetical flooding event around 2020 and the data used is mostly based on scenario analysis and, therefore, lacks practical meaning. The IO model application to indirect economic impact assessment of natural disasters is reviewed in more detail in Chapter 3.

(2) Social Accounting Matrix

SAM is regarded as an extension of the IO models, so, like the IO models, SAM shows similar strengths and weaknesses. It was firstly developed by the 'Cambridge Growth Project' in UK in 1962 and was mainly employed by the World Bank (Stone and Brown, 1962). As a complete data system, SAM represents the interdependence of a socio-economic system by showing the flow data of all economic transactions. Under this consistent framework, both input and output, national and external accounts are taken into account in a square matrix (Pyatt and Round, 1979, Okuyama and Sahin, 2009). Professor Sam Cole made a major contribution to the SAM approach. In order to assess the disaster preparedness and recovery strategies, Cole (1995) extended the matrix of SAM to evaluate the potential hazards' impact caused by tourism and other economic activities on a small Caribbean island. Later, Cole (1998) created multi-country SAM based on economic data on a country level and location data that was extracted from geographical information, and applied it into lifeline failures in the Memphis region. The Event Accounting Matrix (EAM), developed by Cole, Pantoja and Razak (Cole et al., 1993), is one of the biggest improvements to economic research on natural hazards, since it enables the incorporation of direct impacts into the entire SAM and creates a new direction of thinking about the indirect economic impact calculation (Cole, 1998).

(3) Computable General Equilibrium Models

The CGE model, another commonly used approach for secondary economic consequences assessment, is a 'multi-market simulation model based on the simultaneous optimizing behaviour of individual consumers and firms, subject to economic account balance and resource constraints' (Shoven and Whalley, 1992). Rose and Guha (2004) treated CGE is "an extension rather than a replacement of the tradition IO model" (Santos, 2006). Through incorporating policy factors, the basic CGE modelling is popular when analysing the behavioural response to input scarcity and altering market conditions (Rose and Liao, 2005, Okuyama, 2007, Noy and IV, 2016). To overcome the 'business-as-usual' mode, which is a limitation of a basic CGE model, Rose and Liao (2005) improved the industrial production functions by changing the behavioural parameters in the CGE model through optimization of routine and solutions in analytical and numerical ways. As summarised in this study, "This paper advances the CGE analysis of major supply disruptions of critical inputs by: specifying operational definitions of individual business and regional macroeconomic resilience, linking production function parameters to various types of producer adaptations in emergencies, developing algorithms for recalibrating production functions to empirical or simulation data, and decomposing partial and general equilibrium responses".

In recent years, Carrera et al. (2015) developed an integrated methodology based on the CGE model to capture the economic interaction of flooding. The methodology combines a high resolution of spatially explicit damage assessment with macroeconomic loss propagation using a regionally calibrated version of a global CGE model. The authors applied this model to the 2000 Po river flood in Northern Italy by considering three disruption and two recovery scenarios. Their study shows that the regionally disaggregated CGE model is instrumental to tracking how the disaster's effects propagate across regions. The most important characteristic of this model is its flexibility, as it is able to unravel the impact of a disaster into differentiated effects in sub-national economies. Haddad and Teixeira (2015) proposed the SCGE (spatial computable general equilibrium) model, integrating spatial information to estimate flood-induced economic damage in the São Paulo Metropolitan Region in Brazil. Besides calculating the amount of economic impact, SCGE is also able to provide the spatial distribution of economic impacts in affected regions. SCGE is a localized model (Brazil region) since the input CGE data come from a local database and calibration of the model is limited to the Brazil region.

2.3.2.4 Summary

Overall, the first two types, post-disaster economic survey and econometric models, pertaining to Black-box techniques (Albala-Bertrand, 2013), means that we can only observe the input and output data, as the calculation or modelling processes are hidden in a visible black box. They largely rely on primary data sources but neither reflects the changes in economic systems nor captures the interrelationships among economic agents. Additionally, econometric models are highly dependent on time-series data and, as a result, hardly contain any natural disaster experiences. Contrary to black-box techniques, the last one, the economic-based model, uses simulation techniques (Albala-Bertrand, 2013, p.20). This simulation model has a clear explanation on how the economy behaves and operates, and allows for analysis of the interconnections among economic components, such as suppliers and consumers, intermediate goods and demand goods.

Compared with other methodologies, the framework of IO and CGE are more popular since both of them are able to reflect the economic structure of a system by considering inter-industrial and inter-regional linkages at the industrial and economical levels. However, they also have certain disadvantages, as the required data in these two models is quite extensive. With respect to the IO model, although it can provide the inter-industrial linkages, its technological ties are rigid, resulting in a lack of explicit resource constraints and responses to price. Therefore, this method is less appropriate under the situations when market-based mechanisms play a significant role in the economic processes (Bockarjova, 2007). This means that IO modelling does not account for possible substitution of input, regardless of the reasons for altering the input, since the core assumption is that “any affected input will disseminate its scarcity through the whole economy”. Alternative suppliers or input from external sources leads the IO model to overestimate the economic losses.

On the contrary, the CGE model considers the macro-economic context of the markets and allows instantaneous price adjustments, and it is also able to feedback such price effects into economic activities (Carrera et al., 2015). However, the basic assumption of the CGE model is possibilities and it is also overly optimistic regarding market flexibility, in the face of the adaptive capabilities of the real world (Rose, 1995, Carrera et al., 2015). Moreover, even though the CGE model does not rely on an IO table, it requires the exact information of the interaction between input and output markets, as well as adjustment of prices and quantities. Because of the complexity of interactions, fewer sectors are concentrated on CGE modelling than in the IO analysis. CGE can model the individuals and sectors’ optimization response of supply bottlenecks and general changes in the market. More assumptions are included in CGE (Hallegatte, 2008, Hallegatte, 2014, Noy and duPont IV, 2016, Okuyama and Santos, 2014, Rose and Liao, 2005).

Among the four approaches, the IO analysis has its advantage in its simplicity and ability to reflect economic sectors’ interdependencies (Steenge and Bočkarjova, 2007, Hallegatte, 2008, Koks et al., 2016). Its main strength is the ability to differentiate and quantify the economic impacts at an industrial level. As Rose (1995) reveals, “My own use of CGE models has increased my appreciation of input-output economics rather than diminished it”. Furthermore, scholars associated with natural disaster and economy studies, like Okuyama and Santos (2014), Baghersad and Zobel (2015), Noy and IV (2016) also reviewed the model used in disaster impact assessment, and pointed out that, compared with other approaches, the IO analysis is more widely applicable to sudden-onset natural disaster-induced indirect economic loss estimation with the benefits in its simplicities. Previous research of disaster economic consequences assessment based on the IO model show a lack of consideration in changes of productive capacity. Regarding this, Steenge and Bočkarjova (2007) propose to employ 'direct labour input coefficients' to connect labour input and industrial production capacity. However, this model is not able to extract the dynamic change in post-disaster economic recovery. Hallegatte (2008) introduced 'production capacity' factor to link industrial productive capital damage and its production capacity. Hallegatte (2008) proposed a regional adaptive IO model (ARIO) to assess the economic losses of natural disasters at the regional level. The model incorporates the production capacity and adaptive behaviour after the disaster as well as over-production possibilities and import substitutions (Table 1). The ARIO was then applied to analyse the storm surge risks under a sea level rise scenario in Copenhagen (Hallegatte et al., 2011).

2.3.3. Multi-hazard Assessment Methods

Multi-hazard economic impact assessment is still at an early development stage due to the lack of a comprehensive analytical approach. In the Johannesburg Plan, the role of multi-hazard assessment is shown as "An integrated, multi-hazard, inclusive approach to address vulnerability, risk assessment and disaster management, including prevention, mitigation, preparedness, response and recovery, is an essential element of a safer world in the twenty-first century" (UN, 2002) (p.20). As the multi-hazard consists of several natural hazards, it is important to consider impact issues such as how the different relevant hazards influence each other and what elements should be taken into account for various disasters (Marzocchi et al., 2012, Liu et al., 2016).

Among existing related studies, two approaches are applied in multiple natural disasters assessment. One is multi-hazard risk assessment, which the Department for

International Development of UK adopted for multi-hazard disaster risk assessment in order to assist the DFID Business Plan for 2012 to 2015 (DFID, 2012). In this approach, a multi-hazard assessment is constructed on the multi-hazard indexes that are observed from a single-hazard analysis (Kappes et al., 2012). The other is multi-risk assessment (Marzocchi et al., 2012), a more complex approach, analyzing single-disaster risk first and then aggregating them into a multi-risk index (Carpignano et al., 2009). As concluded by Gallina et al. (2016), the steps of multi-hazard risk assessment can be summarized as 'hazard assessment → multi-hazard assessment → exposure assessment of elements at risk → vulnerability assessment → multi-hazard risk assessment'; and for multi-risk assessment is 'hazard assessment → exposure assessment of elements at risk → vulnerability assessment → single-risk assessment → multi-risk assessment'. No matter what approach is applied, the basic quantitative methods for economic impact assessment are similar to those introduced in the previous part (Johnson et al., 2016) (Chapter 1.2.3 and 1.2.4).

2.4. Research Gap

Flood, a global threat for human society and economic systems in particular, can have consequences through direct and invisible impacts via second-hand means. Climate change will cause a growing number of natural disaster occurrences, particularly floods, in the future (Visser et al., 2014, Winsemius et al., 2016). Moreover, rapid urbanization means that more population will be exposed to floods. Therefore, the analysis of the impact of a flood on economies and societies is central to understanding its wide-reaching effects and identifying cost-effective adaptation and mitigation strategies (CRED, 2016). Numerous studies support the argument that natural disaster risk analysis and management, especially of indirect economic impacts assessment, is urgent and necessary for the sustainable development of a country or a city. However, most studies concentrate on the physical features of natural hazards or direct economic loss measurements, and there is a lack of research measuring the indirect economic consequences and modelling post-flood recovery conditions in a given region after a specific single- or multi-flood event. The research gaps can therefore be expressed in the following three points:

1) A dearth of studies that focus on the indirect economic impact assessment of flood-related disasters.

In the existing natural disaster-related studies, economic consequences assessments are restricted to direct economic impact, which mainly refers to the economic losses from affected physical capital or the economic cost that must be used to replace and reconstruct damaged buildings. When concerning the indirect economic consequence, the majority of current assessments prefer to measure the economic aftermath based on statistical data analysis, such as GDP and income, rather than considering the production loss that is produced by alternative economic activities. As indirect economic impact indicators, both GDP and income exclusively show simple economic trends in the affected economy and cannot present a full economic assessment that reflects the complexity of any one economy. A growing number of researches propose the idea that reduction of output within an economy in the aftermath of a disaster event is an effective indicator to demonstrate the disaster-induced indirect economic effects. From this perspective, studies associated with indirect economic influence analysis are still lacking.

2) Lack of a generally accepted methodology to assess flood-induced indirect economic impacts.

Although economic impact estimation is fundamental for natural disaster risk analysis, there is no generally accepted quantitative method to assess indirect economic disaster impacts (Steenge and Bočkarjova, 2007). The relevant studies prefer to measure the economic effects in the affected river basin or related national level. Present research reveals that the region and type of natural disasters determine certain preferences of model application, such as the Dutch-based flood model and the US-based HAZUS model. However**,** when concerning the economic impact, as a large part of economic activities are highly bounded within a regional economic system, the economic impacts of natural disasters are better assessed from the economy rather than the geographical area. In comparison to the previous review, IO models, among all the relevant measurements, are the best option for analyzing flood-induced indirect economic impacts. However, current research in assessing the economic consequences of flood-related disasters based on the IO framework are not able to fully consider the changes of inter-industry relationships and imbalances of an affected economic system during the aftermath of the disaster (Bockarjova, 2007).

Following major disasters, regional economics may be affected and inter-industry relationships may be disrupted (Mechler, 2004). Under the basic theory of IO, total inputs should equal total outputs. Such balance does not exist after a natural disaster happens. For instance, total inputs will no longer equal the total outputs and capital productivity will no longer match total inputs because of the disrupted supply chain. Firstly, as the two main input elements, labour constraints due to labour time loss and industrial capital damage due to natural hazards, can both cause a decrease in labour and capital productivity (Hallegatte and Przyluski, 2010). Since the base assumption of the standard IO model is that the input elements are fixed during the whole process, there is a lack of studies that include the labour constraints and capital damages in the IO framework. Next, consumption behaviour will also change after a disaster (Steenge and Serrano, 2012). People tend to spend more on necessities like food and medical services rather than on luxury goods after a disaster. Such household adaptive consumer behaviour is closely related to total final demand of sectors and ultimately, affects the resources rationing scheme and inter-industry relations. Detecting changing consumption behaviours in the aftermath of a disaster is, therefore, equally crucial in disaster risk analysis.

In addition, there is no common methodology that can be utilized in both individual natural disaster and multi-hazard cases. The multi-hazard approach is still in an early development stage, and its analysis is exclusively limited by quality assessment. Regarding quantitative assessment, practically no adaptive method is able to provide indirect economic impact assessment in the relevant literature. The main challenge is how to quantify the complexity of multiple natural shocks within a specific economy.

3) Poor understanding of post-disaster economic recovery.

After flood disasters, how the imbalanced economy returns to a pre-disaster level or an advanced level significantly corresponds to the resilience of the economy and the external influence from human actions; meanwhile, different recovery paths lead to various economic impacts. Because there is no actual economic data on post-disaster economic recovery, sensitivity analysis of recovery schemes become the only way to provide support for natural disaster mitigation and management at firm, industrial, urban or national levels in the future. However, existing approaches are unable to offer the detailed modelling-process of post-flood recovery that is influenced by exogenous or endogenous factors at weekly, monthly or yearly levels. Although various models are employed for the economic analysis of major natural disasters, in particular at the sectoral level, it seems that the modelling process from these models hidden in a 'black-box', shows no clear and detailed information on how the economy changes, as exogenous or endogenous parameters vary during a certain period.

Only a few methodologies consider the post-disaster recovery scenarios by incorporating adaptive behavior, such as overproduction capacity, alternative labour recovery period and adaptation characteristic times (Li et al., 2013, Koks and Thissen, 2016, Koks et al., 2015b, Hallegatte, 2008). As post-disaster economic recovery is constrained by many factors, more scenarios, such as quality of governance, and alternative recovery plans for certain variables, should be taken into account. Therefore, more options and databases could be offered to policy-makers and stakeholders to mitigate post-flood economic loss and allocate available resources in more effective and efficient ways.

Chapter 3 Indirect Flood Footprint Accounting: Methodology of the Flood Footprint Model

This chapter introduces the main methodology, Flood Footprint Model, established in this thesis to account for the indirect flood footprint of single-and two-flood events. As the Flood Footprint Model has been improved under the Input-output (IO) analysis framework, this chapter starts with a brief introduction of the origin of IO analysis and highlights Leontief's contribution in IO research, followed with the presentation of the basic structure of Leontief's IO model. Since this thesis restricts itself to the indirect economic impact analysis of flood-related disasters, applications and structures of several relevant improved model based on IO are presented as well (Subsection 1.1). Hereafter, Subsection 1.2 offers the overall conceptual framework and structure that underpins the methodology of the Flood Footprint Model for single- and two-flood events through mathematical and logical means. Model variables such as capital and labour constraints, supply bottlenecks and rationing schemes, are analysed as well.

3.1. Input-output Analysis and Natural Disasters

As stated by Leontief (1987), 'Input-output analysis is a practical extension of the classical theory of general interdependence which views the whole economy of a region, a country and even of the entire world as a single system and sets out to describe and to interpret its operation in terms of directly observable basic structural relationships'. Miller and Blair (2009) offer a comprehensive introduction to the structure and applications of the basic Leontief IO model and relevant models. IO analysis is advantageous due to its simplicity and ability to reflect economic sectors' interdependencies (Steenge and Bočkarjova, 2007, Hallegatte, 2008, in den Bäumen et al., 2015). Okuyama and Santos (2014) also reviewed the model used for disaster impact assessment in recent years and note that relative to the other methods, IO analysis is more widely applied to indirect economic loss estimation because of its relative simplicity.

3.1.1. Origin of Input-Output Analysis

IO can be dated back to the seventeenth century, when numerous scholars and classical economists in particular, paid much attention to the development and improvement of IO analysis. As concluded by Kurz and Salvadori (2000), "It is hardly exaggeration to say that input-output analysis is an offspring of systematic economic analysis whose inception is in the seventeenth and eighteenth centuries". The founder of classical Political Economy is considered to be William Pretty (1623-1687), who placed the importance of labour and capital in the production process with the famous dictum "Labour is the Father and active principle of Wealth, as Lands are the Mother" (Petty, 1936, p.68). Meanwhile, he identified 'agricultural surplus' as corn output minus corn input by considering subsistence of labour and raised the view that value can reflect the interrelationship among production, distribution and disposal of the wealth in a given nation (Kurz and Salvadori, 2000). Based on Pretty's work, Richard Cantillon (1697-1734) differentiated a commodity's market price and natural price and proposed the view that the market prices of production may diverge from its natural prices when demand mismatches production. He introduced the concept of 'reproduction' and emphasized that production of land is the basis for human and social survival (Cantillon, 1756, Kurz and Salvadori, 2000).

Later, a French economist François Quesnay (1694-1774) explained the distribution of income through a *Tableau* with two-sector expression of commodities in contemporary France. In 1758, he published the first version of an input-output table, the so-called '*Tableau Economique*', to describe the interconnected flows of national production and consumption in a given year for France. According to '*Tableau*

Economique', a reproduction process was regarded as the entire process of production, distribution and expenditure. Moreover, he made clear distinctions between productive class (e.g. producing in agriculture) and sterile class (e.g. manufacturing process) and concluded that sectors have to rely on each other (Kurz and Salvadori, 2000, Leontief, 1936).

More than a century later, another French mathematical economist Léon Walras, proposed general equilibrium theory as a new direction in economic analysis which was more mathematical. He adopted a 'bottom-up' approach in which the analysis starts with individual markets to study the characteristics of an economy between suppliers and consumers. In addition, he suggested that during economic transactions, suppliers or producers aim to maximize their profits through selling production or services to consumers, while consumers intend to maximize their utilization through providing fixed capital to producers. Since the market contains its own production coefficients and shares the same commodity price, interaction of supply and total demand can lead to an overall general equilibrium (Kurz and Salvadori, 2000, Walras, 2013).

Thanks to contributions by other relevant scholars such as Karl Marx, Vladimir K. Dmitriev, Georg von Charasoff, 'a circular flow' became the core concept of IO analysis (Kurz and Salvadori, 2000). Circularity proposes the idea that social and economic systems contain interconnected and continuous flows of production and services between producer and consumer. Any disruptions will break the balance. For example, decreased output will lead to exceeded demand. Since then, IO has served as the foundation for economic assessment for a given economy, especially in modern national economies (Kurz and Salvadori, 2006, Bockarjova, 2007). In particular, the Russian-American scholar Professor Wassisy Leontief contributed a great deal to IO theory. In 1928, Leontief published his PhD thesis 'Die Wirtschaft als Kreislauf', translated into English as 'The economy as circular flow' (Leontief, 1928, Leontief, 1991). In this thesis, he created input-output tables for the American economy in which the matrix was firstly introduced to *Tableau Economique* to quantify the economic flows. He proposed an appropriate analytical framework, named IO analysis or interindustry analysis, to better apply IO theory.

As a quantitative approach, IO analysis is not only able to quantify the flows and transactions between the basic elements within an economy through a square or rectangular matrix, but also present impacts on altering major variables like technological changes and final demand shifts. Leontief defined his IO method during 1930s-1940s as “an adaptation of the neo-classical theory of general equilibrium to the empirical study of the quantitative interdependence between interrelated economic activities” (Leontief, 1966, p. 134). Later in 1953, Leontief established a dynamic IO model (Leontief, 1953). Through incorporating the capital matrix, which shows the supply-demand transactions among individual sectors, the IO model was able to capture the inter-linkages of multiple sectors. Thus, Leontief’s work provided an improved mathematical foundation for dynamic model development in the future and made it possible to extend the IO approach to multi-industrial work. In recognition of the contribution of IO analysis, Leontief received the Nobel Prize in Economic Science in 1973 (Leontief, 1936).

3.1.2. Basic Leontief Input-Output Model

Leontief was the first person to quantify the regional economy with a matrix expression of flows of production of services among producers and consumers. As a matrix table, the IO table provides the fundamental information for IO analysis by generating economic data of transactions within production and consumption sectors. According to the IO table, the Basic IO model developed by Leontief is able to demonstrate the equilibrium behaviour of economies at regional and national level, for which input and output are balanced. In other words, values of total consumption and total production are the same.

Since this thesis contains a great number of mathematical symbols, formulas and equations, it is important to clarify them at first. Thus, in the following part, bold, upright capital letters are used for matrices, as in $\mathbf{A}$; lower-case bold, upright letters are used for column vectors, as in $\mathbf{x}$, while row vectors are in transposition, indicated by a prime, as $\mathbf{x}'$. A diagonal matrix from vector $\mathbf{x}$ is expressed by a circumflex, as $\hat{\mathbf{x}}$. Italic lower case letters, as x, represents scalars. In this thesis, if the equations contain the same cited number, then these equations are derived from the same original equation. If the equation is a new added equation, then it will be given a new number.

3.1.2.1 Description of Input-output Transactions Table

The basic Leontief IO model is built upon the IO table, in which the economic transactions and industrial interdependence are expressed as monetary values at regional level (e.g. city, state, nation and global). An IO table mainly contains information about commodities in intermediate transactions among sectors and in circle flows from producers to consumers during a specific period, by recording the economic data from official statistic departments or institutions, individual companies or scholars. With the development of IO analysis, as shown in Table 3.1, the structure of IO table is extended to incorporate payments sectors.

Among the IO table with n sectors, the centre part (marked with grey) demonstrates intermediate transactions in all countries. A column vectors stands for the purchasing data (e.g. the value of production that sector j purchased from all sectors), while a row vectors represent the selling data (e.g. the value of production that sector i sold to all sectors). Specifically, taking the sense of z_{ij} as an example, the value of z_{ij} means the amount of input from sector i required for producing outputs x_j in sector j at column level; and from row view, it shows the amount of output of sector i distribute to sector j. Thus, it can say that for producing x_j outputs in sector j, the intermediate demand or required input from all sectors is $\sum_{i=1}^{n} Z_{ij}$. If sector *i* produces output x_i, the intermediate supply or the amount used as input for all sectors is $\sum_{j=1}^{n} Z_{ij}$. The total value of commodities delivered among intermediate flows equals to $\sum_{i=1,j=1}^{n} Z_{ij}$.

Table 3.1. General structure of basic IO table. (Unit: monetary)

		Processing Sectors (purchasing)					Final Demand	Total Output
	Sectors	1	…	*j*	…	*n*		
Processing Sectors (selleing)	1	z_{11}		z_{1j}		z_{1n}	f_1	x_1
	…	…		…		…	…	…
	i	z_{i1}		z_{ij}		z_{in}	f_i	x_i
	…	…		…		…	…	…
	n	z_{n1}		z_{nj}		z_{nn}	f_n	x_n
Payments sector	Value Added	v_1		v_j		v_n		
Total Input		x_1		x_j		x_n		

The right part (marked with green) is *Final Demand*, in which the final consumption on production from each sector is recorded, such as f_i which shows value of household consumption on sector *i*'s production). In principle, final demand refers to household expenditure, governmental consumption, capital inventory/investment and exports. The below row (marked with yellow), labelled *Value Added*, indicates other inputs (exclude the production that used for industrial production process) used for support production, such as payments sectors of employment, capital depreciation, imports and other relevant business taxes (Miller and Blair, 2009)(p.2-3). Like v_j, accounts for the value from other payments sector applied into producing sector *j*'s production of x_j (exclude $\sum_{i=1}^{n} Z_{ij}$). Besides, *Total Input* and *Total Output* specialize the value of production as input or output from the related sectors, respectively. By means of selling and purchasing, it allows production and services flow among industries. The total input x_j of sector *j* equals to the intermediate demand $\sum_{j=1}^{n} Z_{ij}$

plus value added part v_j; the total output x_i of sector *i* is the sum of the intermediate supply $\sum_{i=1}^{n} Z_{ij}$ and final demand f_i.

One important data that generated from the IO table is the *technical IO coefficient* or *direct input coefficient*. It not only quantifies the production efficiency with current technology but also can reflect the dependency of sector *j* in an economy, expressed as a_{ij}, measured as the ratio of value of intermediate demand for sector *j* (z_{ij}) and total input used in sector *j* (x_j) (Eq. 3.1). It is necessary to mention that a significant basic assumption in the basic IO model is that the technical coefficient of each sector is assumed unchanged during the given period.

$$a_{ij} = \frac{z_{ij}}{x_j} \quad \forall j^1. \quad (3.1)$$

3.1.2.2 Mathematical Structure of the Basic Leontief IO Model

The basic IO model, also named as Leontief's model, analyses the economic activities as monetary values of production flows among relevant communities, such as processing sectors and consumers. From a mathematical perspective, the IO model is constructed on a set of linear equations of a closed economic condition (see Table 3.1 which contains *n* sectors, structure of IO model below).

As a row vector illustrates the allocation of output from a particular sector within an economy, the relationship between outputs of sector *i*, and the corresponding intermediate sales/supply (z_{ij}) and final demand in a balanced economy (f_i) can be expressed as Eq.3.2.

$$x_1 = z_{11} + z_{12} + \cdots z_{1j} + \cdots z_{1n} + f_1 = \sum_{j=1}^{n} z_{1j} + f_1$$

$$\ldots$$

1 $\forall j$ is referred to as a universal quantifier, it means that the Eq.3.1 should be applied for each sector *j*.

$$x_i = z_{i1} + z_{i2} + \cdots z_{ij} + \cdots z_{in} + f_i = \sum_{j=1}^{n} z_{ij} + f_i \qquad (3.2)$$

$$\cdots$$

$$x_n = z_{n1} + z_{n2} + \cdots z_{nj} + \cdots z_{nn} + f_n = \sum_{j=1}^{n} z_{nj} + f_n$$

Thus, for *n* sectors, their linkages can be summarized as matrix equation 3.3. Namely, total output for a particular commodity equals to the sum of total intermediate demand and total final demand.

$$\left\{ \begin{array}{l} \mathbf{x} = \begin{bmatrix} x_1 \\ \cdots \\ x_i \\ \cdots \\ x_n \end{bmatrix} \\ \mathbf{Z} = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \cdots & \cdots & \cdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix} \\ \mathbf{f} = \begin{bmatrix} f_1 \\ \cdots \\ f_i \\ \cdots \\ f_n \end{bmatrix} \end{array} \right. \rightarrow \mathbf{x} = \mathbf{Z} + \mathbf{f} \quad (3.3)$$

When introducing the technical IO coefficient a_{ij} in column vectors, intermediate demand of sector *j* to sector *i* (z_{ij}) is measured through Eq.3.4; Eq.3.2 and 3.3 can be written separately as Eq.3.5 and 3.6. Here, **A** stands for the matrix of technical coefficient of the all sectors. It should be noticed that **A** is a non-negative matrix because of $a_{ij} \geq 0$. If the unit of monetary is dollar, the sum of elements in column *j* of **A** means for producing a dollar worth of output of sector *j*, the dollars' worth of inputs that is produced by other sectors. In some cases, part of inputs come from payments sectors, lead to $\sum_{i=1}^{n} a_{ij} < 1$.

$$z_{ij} = a_{ij} x_i \quad (3.4)$$

$$\downarrow$$

$$x_1 = a_{11}x_1 + a_{12}x_2 + \cdots a_{1j}x_j + \cdots a_{1n}x_n + f_1 = \sum_{j=1}^{n} a_{1j}x_j + f_1$$

$$\ldots$$

$$x_i = a_{i1}x_1 + a_{i2}x_2 + \cdots a_{ij}x_j + \cdots a_{in}x_n + f_i = \sum_{j=1}^{n} a_{ij}x_j + f_i \qquad (3.5)$$

$$\ldots$$

$$x_n = a_{n1}x_1 + a_{n2}x_2 + \cdots a_{nj}x_j + \cdots a_{nn}x_n + f_n = \sum_{j=1}^{n} a_{nj}x_j + f_n$$

$$\downarrow$$

$$\mathbf{x} = \begin{bmatrix} a_{\mathbf{11}} & \ldots & a_{\mathbf{1n}} \\ \ldots & \ldots & \ldots \\ a_{\mathbf{n1}} & \ldots & a_{\mathbf{nn}} \end{bmatrix} \mathbf{x} + \mathbf{f} \quad \rightarrow \mathbf{x} = \mathbf{Ax} + \mathbf{f} \qquad (3.6)$$

With the famous notion of *Leontief inverse account* or the *total requirements matrix* $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}$, in which **I** is the n × n identity matrix, Eq.3.6 can be rearranged as Eq.3.7 and 3.8 (Miller and Blair, 2009, p.20). As Eq.3.9, $\mathbf{L} = [l_{ij}]$ can be recognized as the dependency of gross outputs of the economy on the final demand, and each l_{ij} shows the dependency of value of sectoral gross outputs on the sectoral final demands. Meanwhile, **L** also accounts for the impact of the exogenous impact, mainly refers the impact of final demand changes on the amount of industrial gross output.

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{f} \qquad (3.7)$$

$$\downarrow$$

$$\mathbf{x} = \mathbf{Lf} \qquad (3.8)$$

$$\downarrow$$

$$x_1 = l_{11}f_1 + l_{12}f_2 + \cdots l_{1j}f_j + \cdots l_{1n}f_n$$

$$\cdots$$

$$x_i = l_{i1}f_1 + l_{i2}f_2 + \cdots l_{ij}f_j + \cdots l_{in}f_n \qquad (3.9)$$

$$\cdots$$

$$x_n = l_{n1}f_1 + l_{n2}f_2 + \cdots l_{nj}f_j + \cdots l_{nn}f_n$$

3.1.2.3 Basic Assumptions of Leontief IO Model

Several assumptions lead to the basic Leontief IO model as a closed or open demand-driven model. The basic assumption involved in a closed Leontief system is that the economy is a 'self-replacing' system in which the system accounts for all the economic activities. It illustrates that the system exclusively includes the endogenous sectors through translating or moving the exogenous sectors that mainly refer to final demand consumers into the model or system. For instance, as proposed by Miller and Blair (2009), external household demand can be transformed as internal consumed sectors and input sectors in an economy. Meanwhile, in an economic system, all the final demands (including intermediate demands for processing sectors and other final demands for immediate consumption) can be satisfied with the production supplied by the selling sectors (including output from process sectors and other primary inputs from payment sectors). Since the economy is able to provide sufficient production and services, the amount of production in terms of a closed system is larger or equals to the consumption. Thus, production and consumption are balanced as total inputs at least equals to total output of the commodities. Conversely, if the final demand categories are regarded as exogenous variables and **L** is sensitivity to external disturbances in an economy, it pertains to an open system and the IO model becomes an open IO model.

$$\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-\mathbf{1}} \quad (3.10)$$

With respect to a demand-driven model, it assumes that economies are constrained by final demand. Since Eq.3.7 and 3.8 are built upon the measurement of

A as Eq.3.10, unless technology of the sectors changed, **A** is assumed to remain constant during the given period and has no interaction with the economic activities beyond this period. The data of **Z** are merely reliant on the **x** during the whole process. Additionally, **L** links the industrial gross outputs to the corresponding final demand (Miller and Blair, 2009, p.34-41). By contrast, in Ghosh's supply-driven model (1958), shortage of inputs is the main limitation for economic transactions in an economy. In this case, Leontief inversely shows the impact of industrial gross production on the primary inputs. However, the supply-driven model has been questioned by many authors due to the rationality of the model not seeming to respect reality (Miller and Blair, 2009, Aroche Reyes and Marquez Mendoza, 2013, Oosterhaven, 1988).

Other assumptions concern issues like price and input proportions. The model assumes that the same commodities share the same price in the specific period, regardless of producer or consumer sectors. Moreover, production is assumed to hold fixed proportions of inputs in the entire process (Miller and Blair, 2009).

3.1.3. Applications in Natural Disaster Risk Analysis

Input-output (IO) analysis serves as one of the most robust and effective economic techniques with which to quantify the complex interdependencies of industries through industrial economic transactions data in modern economies. With the development of IO analysis, the traditional IO model is routinely applied in economic assessment of various aspects of risk analysis, such as regional and multiregional level, energy and environmental impact analysis, and disaster risk assessment. The Basic IO model acknowledges that multiple intermediate and primary inputs contribute to production processing. Constrained input due to external or internal shocks has to result in changes in production ability and interrupt the flow balance of the given economy. This is when a bottleneck is formed because of the mismatch between supply and demand. Therefore, once a natural disaster leads to a bottleneck in the economy, IO analysis allows the effect and indirect economic impact in particular to be measured. Scholars have contributed a lot to the measurement of disaster impacts through using the Leontief IO model. Below a selection of IO-based models are introduced to demonstrate the development and improvement of the approaches for natural disaster-induced economic loss assessment.

3.1.3.1 The Inoperability Input-Output Model

The *Inoperability Input-Output Model* (IIM) is a methodology to measure "the propagation of perturbations or disturbances throughout a system of interconnected and interdependent infrastructure and economic sectors" (Crowther and Haimes, 2005, Haimes and Jiang, 2001, Santos, 2006). To put it simply, IIM can be used to assess the ripple of economic losses and industrial inoperability caused by immediate shocks to a given sector or several particular sectors. Within the Leontief model framework, Haimes and Jiang (2001) explained the impacts of unauthorized attacks cascaded within a system via its interconnected infrastructures. Infrastructure sectors are those that perform the basic features or functions of a system, and refer to regional basic physical systems such as transportation and energy utilities sectors (Crowther and Haimes, 2005). Inoperability here is defined as a system's inability to fulfil its intended functions, expressed as a percentage relative to the intended state of the system. The formulation of the physically-based IIM is shown as Eq.3.11, although it improved on the Leontief model (Eq.3.6), by adding the superscript *P* (Haimes and Jiang (2001) to represent the disturbance of the economy (caused by natural evens, accidents or willful attacks).

$$\mathbf{x}^{P} = \mathbf{A}^{P}\mathbf{x}^{P} + \mathbf{c}^{P} \quad (3.11)$$

Where $\mathbf{x}^{\mathrm{P}}$ demonstrates the output state, equals to the resulting vector of infrastructures' inoperability; $\mathbf{A}^{\mathrm{P}}$ is the physical interdependency matrix that used to measure the interdependency of the physical subsystems in a large-scale system; $\mathbf{c}^{\mathrm{P}}$ shows the vector of the disturbance input to the interconnected infrastructures.

Since the physical IIM requires numerous data about economic transaction due to building the interconnections of sectors, in order to addressing the data issue, demand- and supply reduction IIMs are constructed with the basic assumption of "economic interdependency data, which reports the annual exchange of commodities between sectors, scaled by producer's prices, is surrogate for logical interdependency data". *Demand Reduction* IIM is a system model developed from Santos and Heimes (2004a) to describe how terrorism-induced perturbations can propagate throughout an entire economic network resulting from system interconnectedness. The equilibrium economic transactional data, which can present logical interdependencies of consumption sectors (among infrastructure and other economic sectors), is set as the datasets of demand-reduction IIM.

$$\mathbf{A}^* = [diag(\hat{\mathbf{x}})]^{-1}[\mathbf{A}][diag(\hat{\mathbf{x}})] \quad (3.12)$$

$$\mathbf{c}^* = [diag(\hat{\mathbf{x}})]^{-1}[\hat{\mathbf{c}} - \tilde{\mathbf{c}}] \leftrightarrow \left\{c_i{}^* = \frac{\hat{c}_i - \tilde{c}_i}{\hat{x}_i}\right\}, \forall i \quad (3.13)$$

$$\downarrow$$

$$\mathbf{q} = [diag(\hat{\mathbf{x}})]^{-1}[\hat{\mathbf{x}} - \tilde{\mathbf{x}}] \leftrightarrow \left\{q_i = \frac{\hat{x}_i - \tilde{x}_i}{\hat{x}_i}\right\}, \forall i \quad (3.14)$$

$$\downarrow$$

$$\mathbf{q} = \mathbf{A}^*\mathbf{q} + \mathbf{c}^* \quad (3.15)$$

Eq.3.15 is structure of the demand-reduction model, in which $\mathbf{A}^*$ is demand-side technical coefficient matrix, stands for the interdependency matrix that derived from *normalized make* and *normalized use* matrices in Bureau of Economic Analysis (BEA) I-O reports (Eq.3.12). BEA is an agency for providing and documenting the industrial economic transactions in the United States, the *make* and *use* matrices show the itemized production and consumption of commodities by various industries, respectively. $\mathbf{c}^*$ indicates the demand perturbation vector and is measured as normalized degraded final demand, such as 'as-planned' final demand minus real final demand $(\hat{\mathbf{c}} - \tilde{\mathbf{c}})$, then divided by the production of 'as-planned' level (Eq.3.13). $\mathbf{q}$ is the inoperability vector and its elements are expressed as the ratios of unrealized production, equals to the gap $(\hat{\mathbf{x}} - \tilde{\mathbf{x}})$ of 'as-planned' production $\hat{\mathbf{x}_i}$ and degraded production $\tilde{\mathbf{x}}$ (Eq.3.14). Here, 'as-planned' operation means the economy without any disruption.

Apart from demand-reduction IIM, another associated model from Santos and Haimes (2004) is *Supply Reduction* IIM. It is also a system model that transformed from supply-side Leontief model (Ghosh Model) but built upon transactional data, which shows the interdependencies among producing sectors. Eq.3.16 accounts for its balance. $\mathbf{A}^{(s)}$ is the supply-side technical coefficient matrix and measured with *make* and *use* matrices from BEA I-O records. $\mathbf{z}^{*}$ is the supply-side primary disturbance, while $\mathbf{q}^{(s)}$ denotes the inoperability from supply reduction.

$$\mathbf{q}^{(s)} = \mathbf{A}^{(s)*}\mathbf{q}^{(s)} + \mathbf{z}^{*} \quad (3.16)$$

Based on the IIM framework, Crowther and Haimes (2005) analysed cascading inoperability and economic impacts due to interdependency in a large-scale economic system with infrastructures and Santos (2006) assessed the impact of an interconnected economic system as a result of disruptive events. Regardless of whether the focus is demand or supply, IIM is an effective approach for measuring disturbance-induced economic losses due to its reliance on economic data. According to Anderson et al. (2004), the results from IIM were within 4% of the estimation made by Anderson's economic consulting team. Consideration of the inoperability of interconnected sectors within an economy has made IIM more useful in risk management through measuring economic loss and inoperability. Moreover, IIM is not only able to describe the impact of the affected sector or sectors on other sectors, but is also extended to capture the economic ripple effect of the disrupted region on other regions. Baghersad and Zobel (2015) improved the IIM to analyse the rationing scheme among industries in the aftermath of a disaster and provided a way to assess indirect economic impact for some specific sectors. However, IIM is still constrained by its assumptions. Firstly, the equilibrium of input and output make IIM unsuitable for economies with large and widespread demand perturbations. The second limitation regards the data source: although BEA generates comprehensive IO related data per five years, the data focuses on the United States. Both the individual sector and the region have to be within the BEA-related area to obtain reliable data. Meanwhile, technical coefficient matrices during periods of less than five years are not accessible and may result in inaccurate results. In addition, the research period has to be long enough to take effect (at least a few hours) and short enough to avoid substitutions (at most, a year). Since expenditure of substitutions from external sectors would change technical multipliers, the research region must be large enough to overcome substitutions issues and to be able to account for interregional substitutions. Moreover, labour constraints are not taken into account (Crowther and Haimes, 2005, Dietzenbacher and Miller, 2015, Okuyama, 2014).

3.1.3.2 Post-disaster Imbalances Model

As most literature has not taken the 'size' of the natural event as a separate factor in risk analysis, Steenge and Bočkarjova (2007) have posited that "the 'size-factor' influences the way society has to think about the recovery and reconstruction process". Indeed, if the natural catastrophe confronting the economy is too large and exceeds the resilience of the system, the post-disaster recovery will become the most serious problem that is faced by the affected region. If both industrial and regional productive capacity decrease due to external shocks, the aftermath imbalances or disproportions of the supply-demand connections will be generated. Hence, Steenge and Bočkarjova (2007) offered a series of basic equations under the IO framework to systematize the economic imbalances in the aftermath of large-scale natural disasters and analyse how the natural disaster impacts on production and consumption capacity, especially with regards to the labour force. Here, the approach is named as

'Post-disaster Imbalances Model'. Household demand is considered as a labour-related input into the economy due to the model built being a closed Leontief model (Eq.3.17). In addition to the IO model assumptions, two other basic hypotheses should be mentioned: one is that the destination of recovery is the pre-disaster level and the other is that a certain percentage of labour is affected after a natural disaster. Thus, the basic equations are showed as below.

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \quad (3.17)$$

$$L = \mathbf{l}'\mathbf{x} \quad (3.18)$$

where **A** means technical coefficient matrix, **x** is column vector of total output and **f** is total demand. The scalar *L* stands for total employment, and **l'** shows the row vector of direct labour input coefficients. Through rearrangement, Eq.3.17 and 3.18 will be performed as:

$$\begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} \quad (3.19)$$

If it assumes

$$\mathbf{h} = \frac{\mathbf{f}}{L} \text{ , } \mathbf{M} = \begin{bmatrix} \mathbf{A} & \mathbf{h} \\ \mathbf{l}' & \mathbf{0} \end{bmatrix} \text{ and } \mathbf{q} = \begin{pmatrix} \mathbf{x} \\ L \end{pmatrix} \text{ , (3.20)}$$

then Eq.3.19 can be shown as

$$\mathbf{Mq} = \mathbf{q} \quad (3.21).$$

Eq.3.21 describes the potential of the economy to self-reproduce with the industrial capacities at level **q**. The left side shows the whole input and the right side is the whole output. The main distinction from the standard closed model is that only sub-matrices **A**, **l'** and **M** are assumed as the fixed coefficients in this model. It means that any changes of **f** will result in new corresponded values of **x** and *L*, and then both Eq.3.20 and 3.21 are changed. For measuring the available production capacity after a natural disaster, (n+1) parameters γ_i ($0 \leq \gamma_i \leq 1$) was introduced to denote the lost fraction of the production capacity in industry *I*, and **c** is the remaining industrial capacities. Thus,

$$\mathbf{c} = (\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} \quad (3.21)$$

$$\text{and} \quad \boldsymbol{\Gamma} = \begin{bmatrix} \gamma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \gamma_{n+1} \end{bmatrix} \quad (3.22)$$

where I is the identity matrix, **Γ** is the (n+1) dimensional matrix (Eq.3.22). Various values of **Γ** lead to different economic conditions as Eq.3.23 and 3.24. If **Γ** is a zero matrix, production capacities remain unchanged from pre-disaster level because there is no influence on the economy. If it is not the zero matrix, only under the condition of $\boldsymbol{\Gamma}\mathbf{q} = \boldsymbol{\gamma}\mathbf{q}$ ($0 \leq \gamma \leq 1$) in the Eq.3.23, the economy's production capacity is shrinking proportionally. If $\boldsymbol{\Gamma} \neq \boldsymbol{\gamma}$, it is not able to replicate the same proportions of input and output.

$$\boldsymbol{\Gamma} \neq \mathbf{0} \quad \rightarrow \; (\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} \neq \mathbf{q} \quad \rightarrow \mathbf{M}(\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} \neq \boldsymbol{\Gamma}\mathbf{q} \quad (3.23)$$

After a natural disaster and flood in particular, total available inputs will become Eq.3.24 due to the influence of production capacities. As measured by Eq.3.25, **t** indicates the accessible inputs for next round (or next time unit) during the post-disaster period. As the core of the 'Basic Equation', Eq.3.25 can be regarded as the immediate situation after a disaster and expresses disturbed proportions among inputs and outputs.

$$\mathbf{M}(\mathbf{I} - \boldsymbol{\Gamma})\mathbf{q} = \mathbf{t} \quad (3.24)$$

$$\begin{bmatrix} a_{11} & \cdots & a_{1n} & h_1 \\ \vdots & \ddots & \vdots & \vdots \\ a_{n1} & \cdots & a_{nn} & h_n \\ l_1 & \dots & l_n & 0 \end{bmatrix} \left(\begin{bmatrix} 1-\gamma_1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & 0 \\ 0 & 0 & 1-\gamma_n & 0 \\ 0 & 0 & 0 & 1-\gamma_{n+1} \end{bmatrix} \begin{bmatrix} q_1 \\ \vdots \\ q_n \\ q_{n+1} \end{bmatrix} \right) = \begin{bmatrix} t_1 \\ \vdots \\ t_n \\ t_{n+1} \end{bmatrix} \quad (3.25)$$

A post-disaster imbalances model allows the consequences of natural disasters to be investigated at both industrial and regional level by considering the *size* impact on interrelations and connections of an economic system from the labour perspective. Since it is a special IO-based model, this approach enables the labour-induced imbalanced linkages between affected production capacity and influenced labour force to be estimated, and recovery possibilities of the broken circular flow in an economy to be examined. Furthermore, this model provides a new direction in terms of thinking about the equilibrium and imbalance that are induced by external disturbances, and expended the influenced factor to the labour force. However, as it only concentrates on the employment impact on economic production, other influencing factors such as damage to physical capital, transportation impacts and changed consumption behaviour in the aftermath of natural disasters, are ignored. This may lead to an incomplete analysis of economic loss and post-disaster recovery.

3.1.3.3 Adaptive Regional Input-Output Model

There are several limitations embodied in IO models due to its rigidity. For example, it cannot illustrate industrial or regional productive capacity situations after an external shock, or respond to the flexibility of economic transactions. Thus, in order to address these constraints, Hallegatte (2008) built an *Adaptive Regional Input-Output Model* (ARIO) to explore the influence of natural disasters and the ensuing recovery phase with consideration of production capacity changes resulting from capital loss-induced and consumption behaviour adaptation. ARIO is a hybrid modelling methodology based upon the earthquake study by Brookshire et al. (1997) and suitable for economies that contain a great number of households with a fixed consumption. The model assumes that either imports or exports are related to outside regions, and imports are available during the entire pre- and post-disaster period. Like other IO-based models, IO tables are the fundamental work of the ARIO due to IO table supporting the interconnections among all the sectors. Below is the basic framework of the ARIO.

$$\bar{Y} = \bar{A}\bar{Y} + \bar{C} \quad (3.26)$$

Eq.3.26 is the basic equation derived from the Leontief IO model, in which $\bar{Y}$ and $\bar{C}$ are the vectors of output and final demand in all industries, respectively. $\bar{A}$ refers the IO table that is modified by removing imports to differentiate the producers of flowed production, which means that the system based on the new IO table is only rely on its own production. The system consists of *n* sectors and total production ($Y(i)$) of industry *i* allocates to other industries used as intermediate consumptions and to other consumers like local final demand ($LFD(i)$), exports ($E(i)$) and reconstruction requirement that includes rebuild demand for damaged capital from industries ($D(i,j)$) and households ($HD(i)$) (Eq.3.27).

$$Y(i) = \sum_j A(i,j)Y(j) + \overbrace{LFD(i) + E(i) + HD(i) + \sum_j D(i,j)}^{\text{Total Final Demand } (TFD(i))} \quad (3.27)$$

Natural disasters is assumed occurred at t=0. As month is the time unit here, ARIO starts from the estimation of industrial available production and total final demand in every month. Thus, in the first month, if there is no any disturbance affect the region, Eq.3.28 obtains industrial production $Y^0(i)$ and first-guess total demand ($TD^0(i)$) should be equal to total production (Eq.3.29). Meanwhile, production of each industry *i* ($Y^1(i)$) is measured as Eq.3.30, where industrial production capacity (Y^{max}) is from pre-disaster industrial output. As Hallegatte et al. (2007) offered the linkages that one value of capital is approximately accounts for four value of value-added, the production capacity, Eq.3.31 can get the amount of Y^{max}, where $\widehat{D}(i)$, $\overline{VA(i)}$ and $\alpha(i)$

is the annual industrial capital damage, annual value-added and overproduce of industrial *i*.

$$Y^0 = (1-A)^{-1}TFD \quad (3.28)$$

$$TD^0(i) = Y^0(i) \quad (3.29)$$

$$\mathbf{Y}^1 = \{Y^1(i)\} \leftrightarrow \left\{Y^1(i) = MIN\{Y^{\max}(i); TD^0(i)\}\right\}, \forall i \quad (3.30)$$

$$\mathrm{Y}^{\max}(i) = \bar{Y}(i)\left[1 - \frac{\widehat{D}(i)}{4\overline{VA}(i)}\alpha(i)\right] (3.31)$$

Hallegatte (2008) constructed a relationship that productive capacity and production capacity in the same industry share the same decreased percentages. Hence, damaged industrial capital may result in degraded production capacities due to disaster shocks. ARIO copes with the issue of production bottlenecks in the aftermath of disaster as followed steps. First-guess amount of orders of industry *i* ($O^1(i)$) means the intermediate demand (commodity) of industry *i* required from other sectors (Eq.3.32). Two scenarios about the connection between the remaining production and first-guess orders are considered. If the available production can satisfy first-guess orders for all sectors, as $Y^1(i) \geq O^1(i)$, then a natural disaster does not arise production bottleneck in the industry *i*. By contrast, if the industry *i* is not able to produce enough commodity, as $Y^1(i) \leq O^1(i)$, external shock produces production bottleneck for this sector and production of other sector *j* is limited by $\frac{Y^1(i)}{O^1(i)}Y^1(j)$. Overall, the new production in each sector *i* ($Y^2(i)$) can be estimated as Eq.3.32.

$$O^1(i) = \sum_j A(i,j)Y^1(j) \quad (3.32)$$

$$\mathbf{Y}^2 = \{Y^2(i)\} =\leftrightarrow \left\{Y^2(i) = MIN\left\{Y^1(i); \text{for all } j, \frac{Y^1(j)}{O^1(j)}Y^1(i)\right\}\right\}, \forall i \ (3.33)$$

Therefore, if $\mathbf{Y}^2 = \mathbf{Y}^1$, there is no bottleneck of the economy and $\mathbf{Y^2}$ is the actual production; if $\mathbf{Y}^2 \neq \mathbf{Y}^1$, bottlenecks are created in the economy and a new total demand is computed as Eq.3.34.

$$TD^1(i) = TFD(i) + \sum_j A(i,j)Y^2(j) \quad (3.34)$$

Through repeating Eq.3.29-3.34, all productions eventually are limited by zero. At this time, the values of total final demand and total production are almost equal to each other, which indicate that the industry *i* is able to supply its relevant demand. During this process, rationing scheme of remaining production allows the economy to mitigate the influence of production bottlenecks. ARIO adopt a mix rationing scheme in which intermediate industrial demand served as priority and other remaining production proportional rationed between total final demand like reconstruction needs and local final demand. However, there are still some special cases for production allocation. For industrial allocation, if intermediate demand of industries cannot be satisfied with accessible production, proportional scheme is also applied as the rationing scheme for all industries' intermediate demand. While in total final demand, although the basic scheme is proportional rationing, the actual distribution is determined by many facts. It implies that household consumption should be support as priority, followed with export and reconstruction needs, since producers of exports can be substituted into suppliers from other regions and rebuild costs either from sectors or from households in the aftermath of natural disasters are assumed repaired by the insurance companies (Hallegatte, 2008).

Regarding the final demand, *adapted local final demand* (*LFD*(*i*)) is linked with original local final demand ($\overline{LFD}(i)$) and dynamic prices of commodities. As Eq.3.35, where M is a macroeconomic indicator and expressed as the ratio of total earnings aftermath to pre-disaster total earnings; *p*(*i*) is the price of the *i*th commodity; and μ stands for the elasticity of local final demand to the production price. Similar approach (Eq.3.36) used to calculate adapted export (*E*(*i*)), but there is no impact of *M*.

$$LFD(i) = M \cdot \overline{LFD}(i) \cdot [1 - \mu(p(i) - 1)] \quad (3.35)$$

$$E(i) = \bar{E}(i) \cdot [1 - \mu(p(i) - 1)] \quad (3.36)$$

Substitution is often assisted with post-disaster recovery. ARIO analyses two substituted cases, one is the industry i with possibility to utilize external production; and the other one is substitution is impossible. For the Eq.3.37, sector is not able to support the whole demand, but possibility for substitution allows both $TD^{\infty}(i)$, $\bar{E}$ and decrease to zero with times $\tau_{LFD}^{\downarrow}$ and $\tau_{E}^{\downarrow}$, respectively (Eq.3.37 and 3.38); in addition, Eq.3.39 shows *A*(*j,i*) reduce with time $\tau_{A}^{\downarrow}$ and Eq.3.40 displays import *I*(*j*) increase with time $\tau_{A}^{\downarrow}$.

$$Y^{\infty}(i) < TD^{\infty}(i) \xrightarrow{substitution} \overline{LFD}(i) - \frac{TD^{\infty}(i) - Y^{\infty}(i)}{TD^{\infty}(i)} \overline{LFD}(i) \frac{\Delta t}{\tau_{LFD}^{\downarrow}} \xrightarrow{\Delta t} \overline{LFD}(i)$$

(3.37)

$$Y^{\infty}(i) < TD^{\infty}(i) \xrightarrow{substitution} \bar{E}(i) - \frac{TD^{\infty}(i) - Y^{\infty}(i)}{TD^{\infty}(i)} \bar{E}(i) \frac{\Delta t}{\tau_{E}^{\downarrow}} \xrightarrow{\Delta t} \bar{E}(i) \quad (3.38)$$

$$Y^{\infty}(i) < TD^{\infty}(i) \xrightarrow{substitution} A(j,i) - \frac{TD^{\infty}(i) - Y^{\infty}(i)}{TD^{\infty}(i)} A(j,i) \frac{\Delta t}{\tau_{A}^{\downarrow}} \xrightarrow{\Delta t} A(j,i) \quad (3.39)$$

$$Y^{\infty}(i) < TD^{\infty}(i) \xrightarrow{substitution} I(j) - \frac{TD^{\infty}(i) - Y^{\infty}(i)}{TD^{\infty}(i)} A(j,i) \frac{\Delta t}{\tau_{A}^{\downarrow}} \xrightarrow{\Delta t} I(j) \quad (3.40)$$

ARIO proved that the flexibility of IO framework allows doing indirect effects investigation through the taking into account of production bottlenecks and various substitution scenarios. As one of the significant contributions in the development of IO analysis and natural disaster impact assessment in particular, parameters considered in ARIO, like how to incorporating the production capacities and production bottlenecks that influenced by natural disasters, served as the basic guidelines for later relevant studies as Li et al. (2013) and Koks et al. (2015a). However, more issues should be considered in this model, such as how to deal with employment effect and household impact in production capacity and in post-disaster recovery process; and how to set the basic assumptions since the most parameters that ARIO relies on are not easy to get real data or response to reality situation.

3.1.3.4 Basic Dynamic Inequalities Model

Li et al. (2013) constructed a Basic Dynamic Inequalities Model (BDI) to assess an imbalanced economic recovery in a post-disaster period by integrated both capital and labour constraints. The core aim for the BDI model is to present a theoretical route map of imbalanced economy recover to pre-disaster level with a series of dynamic inequalities between remaining productive capacities and supply bottlenecks. BDI was built upon the standard IO relationship, as Eq.3.41, in which **x** is sectoral output and **f** is final demand, while **A** is technical coefficients matrix. Labour constraint is introduced from the Basic Equation of *Post-disaster imbalances Model* (Steenge and Bočkarjova, 2007), as Eq.3.42 which come from Eq.3.19-3.21, l represents total regional employment, l' is a row vector about direct labour input coefficients.

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \quad (3.41)$$

$$\left\{\begin{array}{l} \begin{bmatrix} \mathbf{A} & \frac{\mathbf{f}}{l} \\ \mathbf{l}' & 0 \end{bmatrix} \begin{pmatrix} \mathbf{x} \\ l \end{pmatrix} = \begin{pmatrix} \mathbf{x} \\ l \end{pmatrix} \quad (3.19) \\ \mathbf{M} = \begin{bmatrix} \mathbf{A} & \frac{\mathbf{f}}{l} \\ \mathbf{l}' & \mathbf{0} \end{bmatrix} \text{ and } \mathbf{q} = \begin{pmatrix} \mathbf{x} \\ l \end{pmatrix} (3.20) \end{array}\right. \rightarrow \mathbf{M}\mathbf{q} = \mathbf{q} \quad (3.42)$$

$$l = \mathbf{l}'\mathbf{x} \quad (3.43)$$

When the time dynamics and damage fractions added into the Eq.3.41, then both Eq.3.43 and 3.44 indicate the degraded total demand ($\mathbf{x}_{td}^{t}$). While the former one shows it depends on final demand ($\mathbf{f}^t$) over time t, and the latter one illustrates it comes from current production capacity and total final demand, in which **Γ** is the matrix of the damage fraction and expressed as Eq.3.45. It assumes that a natural disaster occurs at time t=0 and the economy consists of n sectors.

$$\mathbf{x}_{td}^{t} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}^{t} \quad (t > 0) \quad (3.43)$$

$$\mathbf{x}_{td}^{t} \approx \mathbf{A}(\mathbf{I}-\boldsymbol{\Gamma}^{t})\mathbf{x}^{0}+\mathbf{f}^{t} \quad (t>0) \quad (3.44)$$

$$\boldsymbol{\Gamma}^{t}=\begin{pmatrix}\gamma_1^t & \cdots & 0\\ \vdots & \ddots & \vdots \\ 0 & \dots & \gamma_n^t\end{pmatrix} \quad (3.45)$$

After dynamics introduced into Eq.3.43, degraded labour production capacity ($\mathbf{x}_l^t$) determined by industrial employment at time t ($\mathbf{I}_e^t$) (measured as Eq.36) and the lost fraction of production capacity in industry *I* ($\gamma_i^t, 0 \leq \gamma_i \leq 1; 1 \leq i \leq n+1$), as shown in Eq.3.47.

$$\mathbf{I}_e^t=(1-\gamma_{n+1}^t)\mathbf{I}_e^0 \quad (3.46)$$

$$\mathbf{x}_l^t=\mathbf{I}_e^t./\mathbf{I} \rightarrow \mathbf{x}_l^t=\left(\hat{\mathbf{I}}\right)^{-1}\mathbf{I}_e^t \quad (3.47)$$

Hence, both Eq.3.43, 3.44 and 3.47 are limited by Eqs.3.48-50, in which the economy balance is constrained by the degraded total production ($\mathbf{x}_{tp}^{t}$) and the balanced total output and labour ($\mathbf{q}^{*(t)}$). $\mathbf{q}^{(t)}$ is an imbalanced indicator of input and output, which determined by total output ($\mathbf{x}_{tp|td|l}^t$) and labour ($l_{tp|td|l}^{t}$) that required for balancing total production capacity, total demand and labour at time t.

$$\mathbf{x}_{tp}^t=l(\mathbf{I}-\boldsymbol{\Gamma}^t)\mathbf{x}^0 \quad (t>0) \quad (3.48)$$

$$\mathbf{M}\mathbf{q}^{*(t)}=\mathbf{q}^{*(t)}, \text{where } \mathbf{q}^{*(t)}=\begin{pmatrix}\mathbf{x}^{*(t)}\\ l^{*(t)}\end{pmatrix} \quad (3.49)$$

$$\mathbf{q}^{*(t)}=\begin{pmatrix}\mathbf{x}^{*(t)}\\ l^{*(t)}\end{pmatrix} \leftarrow \mathbf{q}^{(t)}=\begin{pmatrix}\mathbf{x}_{tp|td|l}^t\\ l_{tp|td|l}^t\end{pmatrix} \quad (3.50)$$

Thanks to the shok of natural disaster, inequalities take place at each time step, as Eq.3.51. Degarded total total production, demand and labour cannot match with each other and then lead to the imblanced economic recovery aftermath.

$$\begin{cases}\mathbf{x}_{td}^t \neq \mathbf{x}_{tp}^t\\ \mathbf{x}_{td}^t \neq \mathbf{x}_l^t\\ \mathbf{x}_{tp}^t \neq \mathbf{x}_l^t\end{cases} \quad (3.51)$$

The above structure comprises the key parts of the BDI model, in which the aftermath condition is clearly presented as inequalities. Li et al. (2013) verified the BDI mode with a hypothetical case of a 2020 London flood. Later, Mendoza-Tinoco et al. (2017) proposed a damage accounting framework that combines the advantages of previous IO-based disaster risk analysis models (particular of the BDI model) and introduced the flood footprint concept to estimate the total economic impact of the 2007 summer floods in the region of Yorkshire and the Humber in the UK. Their methodologies followed the design of ARIO in terms of capturing post-disaster recovery, but with some improvements, such as taking labour availability into consideration during the disaster aftermath. However, damaged industrial and household capital effects in each period are still set as exogenous factors that cannot immediately link and respond to the recovery. Similar to the parameter of import, as it is limited by the transport sector, exogenous import plus exogenous recovery conditions of transportation increase the uncertainty of the results. Thus, current research in assessing the indirect economic consequences of sudden-onset natural disasters based on the IO framework cannot fully accommodate the changes of inter-industry relationships and imbalances of the affected economic system during the aftermath of a disaster (Bockarjova, 2007).

3.1.3.5 Flood Model

Koks et al. (2015a) also employed both imbalanced model and the ARIO model to simulate production loss and economic recovery in a post-disaster economy of the harbour area in Rotterdam (the Netherlands). The so-called *Flood Model* calculates the direct loss through water-depth function (Eq.3.52), and then coverts direct losses to production losses via Cobb-Douglas production function as Eq.3.53. It translates the production input factors capita (K) and labour (L), which also presented as value-added part in IO table, into the amout of output (Y) in sector j. In particular, b indicates the total factor productivity, α and β are output elasticities associated with the changed input. Capital production lossess are esitamted by Eq.3.52, and each sector accounts for the approximated labour lossess since labour assumes evently distributed to sectors.

$$D^{dir} = \sum_{l}^{m} \sum_{r}^{n} \alpha(h_r) D_{l}^{max} \quad (3.52)$$

D^{dir} is total direct damage in the considered area;

D^{max} shows value at risk for land-use type l;

$\alpha_i(h_r)$ represents depth-damage function, h_r is flood-induced water depth of cell r.

$$Y_j = b_j K_j^{\alpha} L_j^{\beta} \quad (3.53)$$

Flood model minimizes the uncertaintiy of the loss transfer process that from dirct damage into indirect damage, or we can say from direct capita damage to indirect value-added loss (the way is shown in Eq.3.54).

$$\Delta Y_j = Y_j - \left[b_j \left(\Delta K_j^{\alpha} \right) \left(\Delta L_j^{\beta} \right) \right] \quad (3.54)$$

ΔY_j is the industrial value-added loss and redefined as reduce industrial production;

ΔK is the remaining capital and ΔL is the remaining labour.

Koks et al. (2015a) built a bridge between industrial value-added and total output of each sector (Eq.3.55). Inoperability of the sector j is expressed as the shock s_j, it is determined by industrial value-added, total output (X_j) and industrial value-added loss. Since Y and X has a fixed link, any changes of ΔY_j will influence s_j via Eq.3.55. For all sectors, a matrix $\boldsymbol{\sigma}$ is used to present the economy-wide inoperability (Eq.3.56). Thus, remaing production capacity matrix $(1 - \boldsymbol{\sigma})$ is evulated in Eq.3.57.

$$s_j = \frac{Y_j}{X_j} \times \frac{\Delta Y_j}{Y_j} \quad (3.55)$$

$$\boldsymbol{\sigma} = \begin{bmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix} \times \begin{pmatrix} s_1 \\ \vdots \\ s_{i+1} \end{pmatrix} \quad (3.56)$$

$$\downarrow$$

$$\mathbf{1}-\boldsymbol{\sigma}=\begin{bmatrix}1-s_1 & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \ldots & 1-s_{i+1}\end{bmatrix} \quad (3.57)$$

During the pre-recovery period, the economy pertain to the conditions of Eq.3.42. if the shock is taking into account, the reamining part of the aftermath system become Eq.3.58, in which $\boldsymbol{t}$ is a row vector in terms of reaming assets and can be regarded as a start-point of the post-disaster recovery.

$$\begin{cases}\begin{bmatrix}\mathbf{A} & \frac{\mathbf{f}}{l}\\ \mathbf{I}' & 0\end{bmatrix}\begin{pmatrix}\mathbf{x}\\ l\end{pmatrix}=\begin{pmatrix}\mathbf{x}\\ l\end{pmatrix} \quad (3.19)\\ \mathbf{M}=\begin{bmatrix}\mathbf{A} & \frac{\mathbf{f}}{l}\\ \mathbf{I}' & \mathbf{0}\end{bmatrix} \text{ and } \mathbf{q}=\begin{pmatrix}\mathbf{x}\\ l\end{pmatrix} (3.20)\end{cases} \rightarrow \mathbf{Mq}=\mathbf{q} \quad (3.42)$$

$$(\mathbf{1}-\boldsymbol{\sigma})\times\mathbf{M}\times\mathbf{q}=\boldsymbol{t} \quad (3.58)$$

Regarding the post-recovery, labour factor at each time period t ($L_{j,t}$) is according to a linear recovery paths and restricted by the maximum demand production capacities among the sectors (Eq.3.59). Remaining capital ($K_{j,t}$) is estimated from Eq.3.60. At each time period, both $L_{j,t}$ and $K_{j,t}$ are inserted to Cobb-Douglas production function to measure the maximum possible industrial value-added. Finally, the economy will return to pre-disaster level and indirect losses can be calucated from Eq.3.61, which defined as sum of the gaps between post-disaster value added and pre-disaster value added during the entire recovery period.

$$L_{j.t}=min\left\{\left(L_j^{pd}+t\times\frac{L_j^0-L_j^{pd}}{\lambda}\right);\left(L_{j.t}\times\frac{X_{j.t}}{X_j^0}\right)\right\}(3.59)$$

L_j^{pd}: post-disaster labour;

L_j^0: pre-disaster labour;

λ: labour recovery period;

$X_{j.t}$: remaining prodcution capacity

X_j^0: pre-disaster production capacity

$$K_{j.t} = K_{j.t-1} - \left(D^{dir}_{j.t-1} - D^{dir}_{j.t-1}\frac{X_{j.t}}{X^0_j}\right) \quad (3.60)$$

L^{pd}_j: post-disaster labour;

L^0_j: pre-disaster labour;

λ: labour recovery period;

$D^{dir}_{j.t}$: the remaining flood damage.

$$D^{ind} = \sum_j^t Y^0_j - \sum_j^t Y_{j,t} \quad (3.61)$$

With a Cobb-Douglas production function, Flood model is able to compute the production capacites that constrained by both labour and capital factors. Meanwhile, it allows to carry out an extensive analyisis analysis for sepcific parameters of the model and provides a more widespread view of the indirect economic impact assessment under the IO framework. However, lack of impacts from import, damaged household and production bottleneck are considered in the flood model. Thus, it is difficult for the model to present a comprehensive economic impact.

Although the balanced growth model has important implications in terms of disproportional damages to industrial production capacity and the post-disaster economic imbalances, the dynamic feature of economic recovery is yet to be fully investigated. An ARIO attempted to capture the post-disaster economic dynamics with particular emphases on price adjustments and adaptations in final consumption, intermediate consumption and production. However, the model neglects important imbalances and the nexus between capital availabilities and labour productivity (Koks et al., 2016). As the assumption of fixed proportions in factor inputs holds throughout the IO model, considering the remaining production seldom based on capital degradation is another drawback. Instead, injuries or excess mortality counts in the labour force should be transformed into degradation in labour availability and productivity.

Table 3.2. Main characterizes of ARIO, BDI, Flood Model and Flood Footprint model.

Model	Productive Capacity of Industry		Import	Consumption Behaviour	Recovery Path			Rationing Scheme	Parameters Considered in Sensitivity Analysis	Relevant Literature
	Capital Damage	Labour Constraints			Industrial Capital	Labour	Household Capital			
Adaptive Regional Input-Output Model (ARIO)	Related with value-added	×	× (Removed imports from original IO table)	Depend on price levels	Exogenous	×	Exogenous	1) Mix scheme Intermediate demand Proportional rationing: exports, final local demand and reconstruction	1) Overproduction capacity 2) Adaptation Characteristic Times 3) Price Dynamics 4) Demand Elasticity 5) Macroeconomic Feedback	Hellagatte (2008, 2014)
Basic Dynamic Inequalities Model (BDI)	Damage fraction = (degraded productive capital)/(total capital stock)	Assumption data	Affected by Transportation Sectors	Exogenous (consumption demand for luxury goods is assumed to be halved after the disaster)	Exogenous	Exogenous	Exogenous	1) Mix scheme Intermediate demand →Proportional rationing: exports, final local demand and reconstruction 2) Priority scheme Intermediate demand � reconstruction� other demand	1) Direct loss of disaster 2) Rationing schemes 3) A regional matrix, alternative labour and household recovery paths	Li et al., 2013; Mendoza-Tinoco et al. (2017)
Flood Risk Model	Depth-damage functions → Capital loss	Cobb-Douglas production function� Direct labour loss	×	Only change in retail and construction sectors	Endogenous	Exogenous	×	1) Priority scheme Intermediate demand →basic demand →reconstruction �other demand �exports	1) Maximum use of regional capacity 2) Recovery period amount 3) Labour recovery period 4) The inventories available per sector 5) Unrestricted stock availability in the construction and retail sector	Koks et al.(2015a); Koks and Thissen (2016)
Flood Footprint Model	Damage fraction = (degraded productive capital)/(total capital stock)	Damage fraction = (degraded labour time loss) / (total labour time)	Affected by Transportation Sectors	Exogenous (basic demand, which need to be satisfied in priority)	Endogenous	Exogenous	Endogenous (covert into industrial capital reconstruction demand)	1) Mix scheme Intermediate demand →basic demand →reconstruction →Proportional rationing: other local demand, exports	1) Labour recovery path 2) Capital recovery scheme 3) Delayed recovery 4) Relationship of labour and capital 5) Import 6) Basic human demand	Developed by this thesis

1. ×: means do not take into consideration; 2. Price is only taken into account in ARIO model, but not in BDI model or Flood Footprint model.

3.2. Methodology for Indirect Flood Footprint Accounting

The 'flood footprint model' developed by this thesis seeks to assess the indirect economic impact of flood-related natural disasters. Relative to previous studies (Hallegatte, 2008, Li et al., 2013), as shown in Table 3.2, the methodology for flood footprint accounting offered here is largely inspired by ARIO and BDI models. With improvements on optimisation of available production imbalances after the disaster, this quantitative methodology framework of indirect flood footprint accounting is able to measure the indirect flood footprint at industrial and regional level in a certain period, produced by two types of flood: 1) a single flood on a single economic system; 2) multiple floods on a single economic system and particular focus on two-flood event.

The specific novelties of the model are as follows:

- It is a quantitative measurement for indirect flood footprint accounting that is able to assess both single-flood and two-flood induced indirect economic impact at both industrial and regional level in a certain period.
- Both industrial and household capital limitations can be regarded as either exogenous or endogenous variables during the post-flood period to different recovery plans.
- The approach to labour impact assessment is more reliable by linking labour constraints with total production capacity.
- It provides a more effective rationing scheme of available resources in the aftermath of floods with considerations on basic human requirements and industrial interdependencies.
- It allows various types of sensitivity analysis to model parameters and other external influences such as quality of post-flood governance, due to the flexibility of the model in which recovery process can be clearly simulated.

3.2.1. Overall Conceptual Framework

The flood footprint modelling framework is designed to capture the overall indirect impacts on a regional economy and simultaneously capture the industry interdependencies, post-disaster economic inequalities, household adaptive consumption behaviour, and effects of capital damages and labour constraints on production capacity during post-disaster recovery and supply bottlenecks. Flood Footprint Model is a further development based upon Li et al. (2013), and it starts with a standard Leontief demand-driven IO model (Leontief, 1936; Miller and Blair, 2009), which records the transaction flows between producers and consumers and takes the following form:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \quad (3.6)$$

where **x** denotes the industrial output; **f** is final consumption demand, including local household consumption, government expenditure, capital inventory and exportation; and **A** is the technical coefficient, which is assumed to be fixed throughout the economy. The left-hand side of Eq.3.6 is the total output of the economy, while the right-hand side is the total demand of the economy.

Two basic assumptions are embodied among Flood Footprint Model. One is that imports can be substituted by domestic productions before the disaster, it means that pre-disaster situation does not consider the outside inputs for maintain the circular flow, which is the theory followed with Von Neumann (1971). The other one is that imports as an external resources, are allowed for contributing to post-flood economic recovery allows imports during the entire recovery period. Thus, before flood occurs, local production ($\mathbf{x^0}$) can satisfy intermediate demand ($\mathbf{Ax^0}$) and final consumption demand ($\mathbf{f^0}$) at the same time (Eq.3.62).

$$\mathbf{x^0} = \mathbf{A}\mathbf{x^0} + \mathbf{f^0} \quad (3.62)$$

$$\mathbf{f^0} = \mathbf{f^0_{hh}} + \mathbf{f^0_{gov}} + \mathbf{f^0_{cap}} + \mathbf{f^0_{exp}} \quad (3.63)$$

where **A** represents domestic coefficients and describes the dependence of each sector and $\mathbf{f^0}$ is the final demand (Eq.3.63) including household demand ($\mathbf{f^0_{hh}}$), government demand ($\mathbf{f^0_{gov}}$), capital inventory ($\mathbf{f^0_{cap}}$) and exportation ($\mathbf{f^0_{exp}}$).

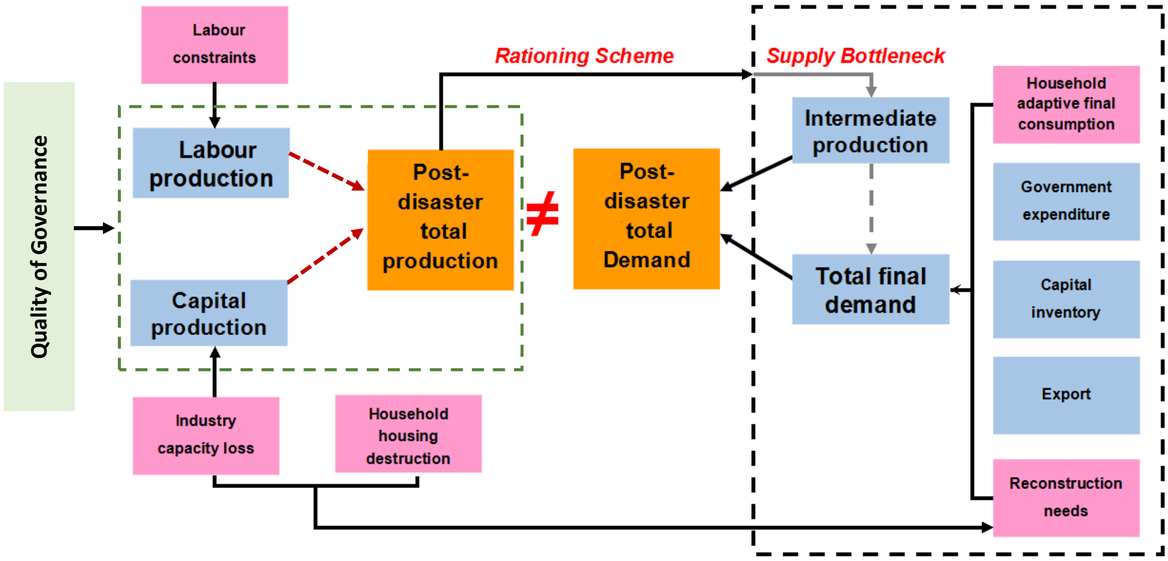


Figure 3.1. Post-disaster imbalanced economy and recovery.

Such balances will break up after the disaster because of its influence on capital and labour. As the proportions of all inputs are assumed to be fixed in the basic IO model, capital damage and labour constraints due to the shock lead to decreases in the industrial capital and labour input, implying that capital production capacity and labour production capacity do not necessarily shrink proportionally. Thus, a series of inequalities (Eq.3.64) can be observed from the equations below (Figure 3.1): 1) Degraded post-disaster total production (x_{pro}) does not match post-disaster total demand (x_{dem}) (which is denoted with 'non-equality' sign in Figure 1). 2) Degraded labour production capacity (x_{lab}) does not match degraded capital production capacity (x_{cap}). 3) Degraded labour/capital production capacity does not match degraded total production (which is denoted by red dashed arrows in Figure 4.1). Despite these inequalities, the quality of governance also have influence on the whole economic systems, effective governance encourages the recovery of production capacity while bad or incompetent governance resulted in reduction of industrial capacity.

$$\begin{cases} x_{pro} \neq x_{dem} \\ x_{lab} \neq x_{cap} \\ x_{pro} \neq x_{lab} \\ x_{pro} \neq x_{cap} \end{cases} \quad (3.64)$$

When the destroyed capital and affected labour are recovered, the whole economy will have returned to pre-disaster levels, implying that the remaining production alone is sufficient to meet intermediate industrial demand and original final demand; the indirect effects of the disaster end, and we enter the recovery period.

During this process, five points should be analysed in the Flood Footprint Model: capital damage, labour constraints, household consumption behaviour, supply bottleneck and rationing scheme, in particular, primary endogenous factors embodied in the Flood Footprint Model are shown in Table 3.3. Below Section 3.2.2 and 3.2.3 present the detailed introduction about the variables in Flood Footprint Model for single-and two-floods' indirect flood footprint accounting.

Table 3.3. Primary endogenous factors in the Flood Footprint Model.

Model Parameters	Indicators	*t*=0 (Direct influence by flood)		*t*>0 (Post-flood recovery)	
		Endogenous	Exogenous	Endogenous	Exogenous
Rationing Scheme					√(determined by model managers/policy-makers)
Capital Limitation	α^t : damage fraction of capital productivity		√ (affected by direct physical damage)	√ (if there is no other recovery plan)	√(determined by model managers/policy-makers)
Labour Constraints	θ^t : damage fraction of labour productivity		√(affected by direct labour time loss)		√(determined by model managers/policy-makers)
Import	y_{imp}^t		√ (affected by transport sector)	√ (if there is no other recovery plan)	√(determined by model managers/policy-makers)
Basic Demand	f_{cd}^t		√ (determined by model managers/policy-makers)		√(determined by model managers/policy-makers)

3.2.2.Model Variables for Single Flood Event

Both capital and labour limitations of industrial production capacity are inspired by the 'Event Matrix', a special matrix used to demonstrate the effect of a natural disaster. As Cole et al. (1993, p.4-7) explained, "In the most general case, the event matrix will be a set of tables corresponding to entries in the original I-O table which specifies i) the extent of damage to internal and external components, ii) the goal for recovery, and iii) the time scale for recovery. The detail of how an event matrix is specified will depend on the situation under investigation".

3.2.2.1 Capital Limitations

Capital losses include industrial capital loss and household capital loss. Industrial capital loss leads to reduction in production activities, while household capital loss does not impact production activities but needs to be repaired/replaced during recovery. In any real case, information concerning destroyed industrial capital can be obtained from insurers or government statistics. Household capital damage information is difficult to obtain because of privacy protection, although insurers hold this information. Since this capital is typically within the sectors of electronics, general equipment, transportation equipment, manufactured products and construction and maintenance services, we can allocate the damaged capital of household into the related sectors and then turn to industrial damaged capital.

Capital constraints are added into the model to estimate the influence of industrial capital production on the local economy. Destroyed capital has a negative influence on the production process and could result in decreased industrial production capacity. Thus, the production constrained by capital damage at time t ($\mathbf{x}^{\mathbf{t}}_{\mathbf{cap}}$) is shown in Eq.3.65.

$$\mathbf{x}_{\mathbf{cap}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_{\mathbf{1}}}^{t}\right)\mathbf{x}^{\mathbf{0}} \ (t \geq 1) \quad (3.65)$$

where $\widehat{\boldsymbol{\alpha}_{\mathbf{1}}}^{t}$ is the diagonal matrix of industrial damage fractions at time t, α is estimated as the ratio of damaged industrial capital to industrial original capital stock, $\mathbf{x}^{\mathbf{0}}$ is the pre-disaster output level, and t is the time unit, when t=1, it stands for the first period after the flooding occurred.

3.2.2.2 Labour Constraints

According to a previous study (Steenge and Bočkarjova, 2007), labour as one of the input elements can be introduced into the standard IO model (Eq.3.66),

$$L = \mathbf{l}'\mathbf{x} \quad (3.66)$$

$$\downarrow$$

$$\mathbf{x^0} = (\mathbf{l}')^{-1}L \quad (3.67)$$

$$\downarrow$$

$$\mathbf{x_{lab}^t} = (\mathbf{l}')^{-1}\underbrace{\left((\mathbf{1}-\boldsymbol{\beta}^t)L\right)}_{avaliable\ L} \rightarrow \mathbf{x_{lab}^t} = \left(\mathbf{I}-\widehat{\boldsymbol{\beta}}^t\right)((\mathbf{l}')^{-1}L) \quad (t \geq 1) \quad (3.68)$$

$$\downarrow$$

$$\mathbf{x_{lab}^t} = \left(\mathbf{I}-\widehat{\boldsymbol{\beta}}^t\right)\mathbf{x^0} \quad (t \geq 1) \quad (3.69)$$

where *L* is the total employment, and **l'** represents direct labour input coefficients. Such equilibrium will be broken when the region is suffering a disaster. The change of final demand (**f**) resulted in different *L* and **x**. Thus, the linear relationship between labour and productivity of industry are applied here. This thesis introduce the damage fraction of labour productivity ($\beta_1{}^t$) into the model, similar to Eq. 3.65, the actual production limited by labour constraints ($\mathbf{x^t_{lab}}$) becomes Eq.3.69.

3.2.2.3 Basic Demand

Household adaptive consumption behaviour during flood aftermath is set exogenously[2]. We often assume that life necessities in the disaster aftermath tend to gain greater significance, also called basic demand *(*$\mathbf{f_{cd}}$), which belongs to the final demand in the Flood Footprint Model and is equal to the minimum amount of specific sectors. The amount or share of $\mathbf{f_{cd}^t}$ in a period t thereby depends on policy makers, which are assured that consumers will accept

2 It means that household consumption after the disaster will accept what is exogenously decided.

their decisions. Regardless of the amount of $\mathbf{f_{cd}^t}$, residual production allocation in each round[3] has priority.

3.2.2.4 Supply Bottleneck

A new component called recovered demand ($\mathbf{f_{rec}}$) (Eq.3.70), consisting of industrial capital recovery demand ($\mathbf{f_{ID}}$) and household recovery demand ($\mathbf{f_{HD}}$), is added to the final demand part (Eq. 3.71), and the total required production ($\mathbf{x_d}$) is calculated by the new final demand ($\mathbf{f_d}$) (Eq. 3.72).

$$\mathbf{f_{rec}} = \mathbf{f_{ID}} + \mathbf{f_{HD}} \qquad (3.70)$$

$$\mathbf{f_d} = \mathbf{f_{hh}^0} + \mathbf{f_{gov}^0} + \mathbf{f_{cap}^0} + \mathbf{f_{exp}^0} + \mathbf{f_{rec}} \quad (3.71)$$

$$\mathbf{x_d} = \mathbf{A}\mathbf{x_d} + \mathbf{f_d} \qquad (3.72)$$

Economic linkages among sectors will also be disturbed in the disaster's aftermath because of capital loss and labour constraints. Damage of industrial capital, decreased industrial capital productivity and labour constraints reduce the productivity of labour. The decreased productivity of the two main inputs, capital and labour, results in decreased domestic product. Building on Eqs. 3.65 and 3.69, maximum production capacity limited by capital loss ($\mathbf{x^0_{cap}}$) in the first round after the disaster is shown in Eq. 3.73, and maximum production under labour constraint ($\mathbf{x^0_{lab}}$) in Eq. 3.74.

$$\mathbf{x_{cap}^1} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_1{}^1}\right)\mathbf{x^0} \quad (3.73)$$

$$\mathbf{x_{lab}^1} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta}_1{}^1}\right)\mathbf{x^0} \quad (3.74)$$

In order to consider both capital and labour limitations, the available production is the minimum among the productions of capital and labour constraints (Eq. 3.75). The labour I considered in Eqs. 3.66-69 refers to the sector-specific working population, and there is no workforce transfer among sectors[4].

3 In terms of mathematical meanings, 'Round' here and 'period' in this paper are used to mean the remaining products including available imports are fully allocated into economic systems; in the real case, it refers to the time unit/period, i.e. week, month or year.

[4] We did not consider that an electrician may switch to an IT job, but in reality, this transfer may occur.

$$\mathbf{x^1} = \min(\mathbf{x^1_{cap}}, \mathbf{x^1_{lab}}) \quad (3.75)$$ [5]

The total required production exceeds the available production ($\mathbf{x_d} > \mathbf{x^1}$) implying that the remaining production cannot support intermediate and final demand simultaneously, which then results in a supply bottleneck.

3.2.2.5 Rationing Scheme

Lower productivity leads to less production, and importation becomes the only way to meet the reconstruction needs of industrial and household capital. Import refers to the external input for the recovery demand, and it exists only when the local economic equilibrium is absent. Imports here are closely related to the capacity of the transportation sectors. As the capacity of the transport sector recovers, import also increases. The amount of imports at period t ($\mathbf{y^t_{imp}}$) depends on the remaining capacity of the transportation sector (Eq. 3.76-78). Here it assumed that the maximum capacity of import in the flooded area is $\mathbf{y^0_{imp}}$, and for supporting the capital damage demand and basic demand, imports are always provided during the whole disaster recovery period[6]. The whole recovery period starts from *t*=1, and *t* is the time unit, such as week, month or year.

$$\mathbf{y^1_{imp}} = \left(1 - \alpha^1_{1\_tran}\right)\mathbf{y^0_{imp}} \quad (3.76)$$

$$\mathbf{y^2_{imp}} = \left(1 - \alpha^2_{1\_tran}\right)\mathbf{y^0_{imp}} \quad (3.77)$$

…

$$\mathbf{y^t_{imp}} = \left(1 - \alpha^t_{1\_tran}\right)\mathbf{y^0_{imp}} \quad (t \geq 1) \quad (3.78)$$

Where α^t_{tran1} is the fraction of damaged transport sector capital at time period *t* times the original import ($\mathbf{y^0_{imp}}$); $\mathbf{y^0_{imp}}$ is the amount of imports based on the pre-disaster transport level.

If import has been taken into account, then the total available production at the beginning stage of the recovery period is $(\mathbf{x^1} + \mathbf{y^1_{imp}})$. Because I assume that available production should first be sufficient for inter-industry demand and then goes into final demand, the complete recovery analysis will be based on scenarios 1 and 2 shown in Figure

[5] $\mathbf{x^1}$ selects for each element the smallest corresponding element of the vectors $\mathbf{x^t_{cap}}$ and $\mathbf{x^t_{lab}}$.

[6] Here, it is assumed that import stays exogenous through the whole process.

3.2. Such rationing scheme is one kind of very general production allocated ways, and it can be adjusted according to different scopes and conditions, like proportional rationing scheme.

(1) **Scenario 1**: recovery of intermediate linkages (Eq. 3.79).

$$\mathbf{x^1} + \mathbf{y^1_{imp}} < \mathbf{Ax^0} + \mathbf{f^1_{cd}} \quad (3.79)$$

If $\left(\mathbf{x^1} + \mathbf{y^1_{imp}} < \mathbf{Ax^0}\right)$ (3.80), then all the available production should be used to recover intermediate demand. Several rounds are run until the original industrial demands are satisfied. As primary inputs must be used in fixed proportions in a standard IO model, a balance between capital and labour capacities should be restored first so that the production level can then be raised back to the pre-disaster level. The details of the rationing scheme are shown below.

Round 1[7]

Imports (Eq. 3.77) are added because basic demand for minimal human needs ($\mathbf{f^1_{cd}}$, whose data depends on model managers or policy makers) is taken into account, and at the same time, when considering the the maximum capacity[8] of the economic system, the available production ($\mathbf{x^1_{rem}}$) in Round 1 becomes

$$\mathbf{x^1_{rem}} = \min\left(\mathbf{x^1} + \mathbf{y^1_{imp}}, \mathbf{x^0} + \mathbf{y^0_{imp}}\right) \quad (3.81)$$

To repair the industrial capital damage, the residual final demand ($\mathbf{f^1_{rem}}$), which excludes the basic demand of Round 1 (Eq. 3.82), is used first for industrial capital recovery ($\mathbf{f^1_{rec}}$; Eq. 3.83) and then for other final demand ($\mathbf{f^1_{others}}$, Eq. 3.84)[9].

If the remaining final demand is not able to satisfy the basic demand, i.e. if $\mathbf{f^1_{rem}}$ is smaller than $\mathbf{f^1_{cd}}$, the allocation of the goods between the capital damage recovery demand and basic demand should be adjusted according to the different situations. $\mathbf{f^1_{others}}$ can include several users (similar to Eq. 3.63), and the proportion of each part is determined by the recovery preferences.

$$\mathbf{f^1_{rem}} = \mathbf{f^1} - \mathbf{f^1_{cd}} \quad (3.82)$$

[7] 'Round 1' here means the first time period (first week/first month) after the disaster shocked.

[8] In the original transactions, it is assumes that import can be substituted by domestic goods or services, so when considering imports, the maximum capacity of the sector is the sum of domestic production and imports.

[9] Recall that in this case, we do not consider the competition among all final demand users.

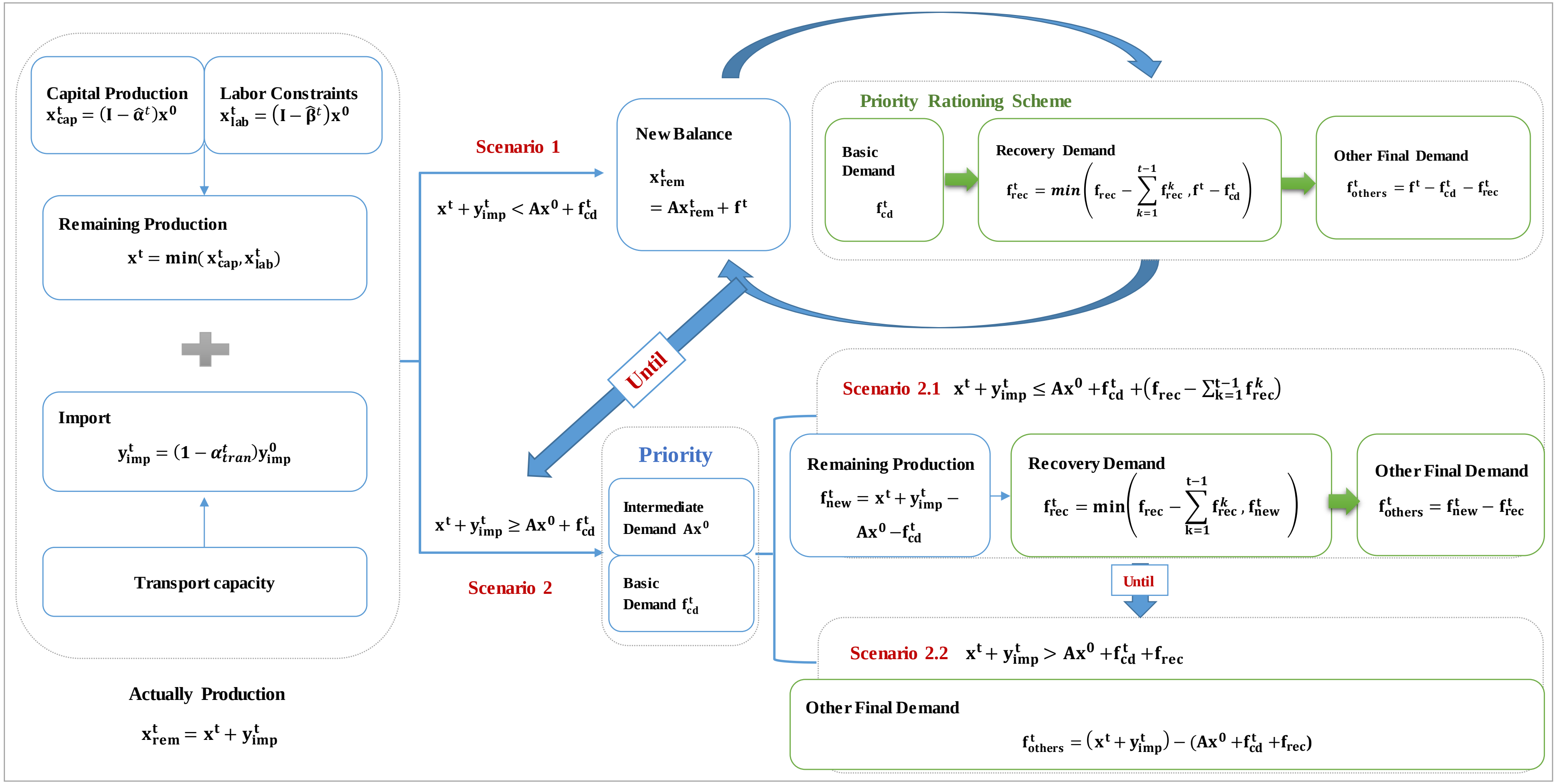


Figure 3.2. Rationing scheme of the Flood Footprint Mode in mathematical ways.

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{1}} = \min(\mathbf{f}_{\mathbf{rec}}, \mathbf{f}_{\mathbf{rem}}^{\mathbf{1}}) \quad (3.83)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{1}} = \mathbf{f}_{\mathbf{rem}}^{\mathbf{1}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{1}} \quad (3.84)$$

Capital damage fractions in the next round ($\boldsymbol{\alpha}^{\mathbf{2}}$), which considers the recovered industrial capital ($\mathbf{f}^{\mathbf{1}}_{\mathbf{rec}}$), are calculated by Eq. 3.85, where $\mathbf{s}^{\mathbf{0}}_{\mathbf{cap}}$ is the original industrial capital stock.

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{2}} = \left(\widehat{\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}}}\right)^{-1}(\mathbf{f}_{\mathbf{rec}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{1}}) \quad (3.85)$$

Round 2

Production limited by industrial capital loss ($\mathbf{x}_{\mathbf{cap}}^{\mathbf{2}}$) and labour constraint ($\mathbf{x}_{\mathbf{lab}}^{\mathbf{2}}$) in Round 2 is quantified by Eq. 3.86 and 3.87, respectively. The available production is also based on Eq. 3.88.

$$\mathbf{x}_{\mathbf{cap}}^{\mathbf{2}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_{\mathbf{1}}}^{\mathbf{2}}\right)\mathbf{x}^{\mathbf{0}} \quad (3.86)$$

$$\mathbf{x}_{\mathbf{lab}}^{\mathbf{2}} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta}}_{\mathbf{1}}{}^{\mathbf{2}}\right)\mathbf{x}^{\mathbf{0}} \quad (3.87)$$

$$\mathbf{x}^{\mathbf{2}} = \min(\mathbf{x}_{\mathbf{cap}}^{\mathbf{2}}, \mathbf{x}_{\mathbf{lab}}^{\mathbf{2}}) \quad (3.88)$$

Then, in the same way as Round 1, the new balance is

$$\mathbf{y}_{\mathbf{imp}}^{\mathbf{2}} = (1 - \alpha_{1\_tran}^{2})\boldsymbol{y}_{\boldsymbol{imp}}^{\mathbf{0}} \quad (3.89)$$

$$\mathbf{x}_{\mathbf{rem}}^{\mathbf{2}} = \min\left(\mathbf{x}^{\mathbf{2}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{2}}, \mathbf{x}^{\mathbf{0}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{0}}\right) \quad (3.90)$$

The allocation of final demand ($\mathbf{f}^{\mathbf{2}}$) is

$$\mathbf{x}_{\mathbf{rem}}^{\mathbf{2}} = \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{2}} + \mathbf{f}^{\mathbf{2}} \quad (3.91)$$

$$\mathbf{f}^{\mathbf{2}} = \mathbf{x}_{\mathbf{rem}}^{\mathbf{2}} - \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{2}} \quad (3.92)$$

$$\mathbf{f}_{\mathbf{rem}}^{\mathbf{2}} = \mathbf{f}^{\mathbf{2}} - \mathbf{f}_{\mathbf{cd}}^{\mathbf{2}} \quad (3.93)$$

The rest of recovery demand is the gap between total recovery demand ($\mathbf{f}_{\mathbf{rec}}$) and total recovered part before this round ($\sum_{k=1}^{t-1} \mathbf{f}_{\mathbf{rec}}^{k}, , t \geq 1$). Hence, in the Round 2, the remaining required demand for recovery equals to ($\mathbf{f}_{\mathbf{rec}}$-$\mathbf{f}_{\mathbf{rec}}^{\mathbf{1}}$).

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{2}} = \min(\mathbf{f}_{\mathbf{rec}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{1}}, \mathbf{f}_{\mathbf{rem}}^{\mathbf{2}}) \quad (3.94)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{2}} = \mathbf{f}_{\mathbf{rem}}^{\mathbf{2}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{2}} \quad (3.95)$$

The capital damage fraction of the next round is

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{3}} = \left(\widehat{\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}}}\right)^{-1}\left(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{\mathbf{2}} \mathbf{f}_{\mathbf{rec}}^{k}\right) \quad (3.96)$$

…

Round t (Eq.3.97 to 3.104) is characterized as follows:

$$\mathbf{x}_{\mathbf{cap}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_{\mathbf{1}}}^{\mathbf{t}}\right)\mathbf{x}^{\mathbf{0}} \quad (3.65)$$

$$\mathbf{x}_{\mathbf{lab}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta}_{\mathbf{1}}}^{\mathbf{t}}\right)\mathbf{x}^{\mathbf{0}} \quad (3.69)$$

$$\mathbf{x}^{\mathbf{t}} = \min(\mathbf{x}_{\mathbf{cap}}^{\mathbf{t}}, \mathbf{x}_{\mathbf{lab}}^{\mathbf{t}}) \quad (3.97)$$

$$\mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} = (1 - \alpha_{1\_tran}^{t})\mathbf{y}_{\mathbf{imp}}^{\mathbf{0}} \quad (3.78)$$

$$\mathbf{x}_{\mathbf{rem}}^{\mathbf{t}} = \min\left(\mathbf{x}^{\mathbf{t}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{t}}, \mathbf{x}^{\mathbf{0}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{0}}\right) \quad (3.98)$$

$$\mathbf{x}_{\mathbf{rem}}^{\mathbf{t}} = \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{t}} + \mathbf{f}^{\mathbf{t}} \quad (3.99)$$

$$\mathbf{f}^{\mathbf{t}} = \mathbf{x}_{\mathbf{rem}}^{\mathbf{t}} - \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{t}} \quad (3.100)$$

$$\mathbf{f}_{\mathbf{rem}}^{\mathbf{t}} = \mathbf{f}^{\mathbf{t}} - \mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} \quad (3.101)$$

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{t}} = \min(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{t-1} \mathbf{f}_{\mathbf{rec}}^{k}, \mathbf{f}_{\mathbf{rem}}^{\mathbf{t}}) \; (t \geq 1) \quad (3.102)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{t}} = \mathbf{f}_{\mathbf{rem}}^{\mathbf{t}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{t}} \quad (3.103)$$

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{t+1}} = \left(\widehat{\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}}}\right)^{-1}(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{\mathbf{t}} \mathbf{f}_{\mathbf{rec}}^{k})(t \geq 1) \quad (3.104)$$

…

Until $\left(\mathbf{x}^{\mathbf{t}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} \geq \mathbf{A}\mathbf{x}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{t}}\right)(t \geq 1)$ (3.105), then go to scenario 2.

(2) **Scenario 2**: recovery of final demand (Eq. 3.105).

$$\mathbf{x}^{\mathbf{t}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} \geq \mathbf{A}\mathbf{x}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} \quad (3.105)$$

If $\left(\mathbf{x^t}+\mathbf{y^t_{imp}} \geq \mathbf{Ax^0}+\mathbf{f^t_{cd}}\right)$ (3.105) , the available production has already satisfied intermediate industrial demand ($\mathbf{Ax^0}$and other production can be delivered for final demand. Here, two points should be considered. The first is recovery demand. As capital reconstruction is the fundamental requirement of economic recovery, recovery demand should be treated as the priority. The second is basic demand. Apart from recovery demand, some necessities are basic human needs. Production should also be allocated to such basic demand according to the different requirement levels in each time period. According to the conditions of the remaining production, scenarios 2.1 and 2.2 are analysed below (where $\mathbf{x^t}$ is same as Eq. 3.65, 3.69 and 3.97, and $\mathbf{y^t}_{\mathbf{imp}}$ is estimated by Eq. 3.78).

① **Scenario 2.1**

$$\mathbf{Ax^0}+\mathbf{f}^t_{\mathbf{cd}} < x^{\mathbf{t}}+\mathbf{y^t_{imp}} \leq \mathbf{Ax^0}+\mathbf{f^t_{cd}}+(\mathbf{f_{rec}}-\textstyle\sum_{k=1}^{t-1}\mathbf{f}^k_{\mathbf{rec}})\ (t \geq 1) \quad (3.106)$$

In this situation, current production is sufficient for intermediate demand but cannot satisfy recovery demand and basic demand at the same time. Thus, other rest of production is used to support recovery demand and basic demand in the first step. Recovery demand $\mathbf{f^t_{rec}}$is calculated as Eq. 3.108, and basic demand $\mathbf{f^t_{cd}}$ is calculated as Eq. 3.107.

$$\mathbf{f^t_{new}} = \min\left(\mathbf{x^t}+\mathbf{y^t_{imp}}, \mathbf{x^0}+\mathbf{y^0_{imp}}\right) - \mathbf{Ax^0} - \mathbf{f^t_{cd}} \quad (3.107)$$

$$\mathbf{f^t_{rec}} = \min(\mathbf{f_{rec}}-\textstyle\sum_{k=1}^{t-1}\mathbf{f}^k_{\mathbf{rec}}, \mathbf{f^t_{new}}\ )\ (t \geq 1) \quad (3.108)$$

$$\mathbf{f^t_{others}} = \mathbf{f^t_{new}} - \mathbf{f^t_{rec}} \quad (3.109)$$

$$\boldsymbol{\alpha_1}^{\mathbf{t+1}} = \left(\widehat{\mathbf{s^0_{cap}}}\right)^{-1}(\mathbf{f_{rec}}-\textstyle\sum_{k=1}^{t}\mathbf{f}^k_{\mathbf{rec}})(t \geq 1) \quad (3.110)$$

…

This situation holds until $\sum_{k=1}^{t}\mathbf{f}^k_{\mathbf{rec}} = \mathbf{f_{rec}}\ (t \geq 1)$ (3.111) and $\boldsymbol{\alpha}^{\mathbf{t+1}} = 0$ (3.112). We then come to scenario 2.2.

② **Scenario 2.2**

$$\mathbf{x^t}+\mathbf{y^t_{imp}} > \mathbf{Ax^0}+\mathbf{f^t_{cd}}+\mathbf{f_{rec}} \quad (3.113)$$

When current production has met intermediate, recovery and basic demand, the rest of production is used to support other final demand. Equations for allocating available resources for each part of the final demand depend on different rationing schemes. Take a proportional rationing scheme as an example. At time period t, the recovery demand $\mathbf{f_{rec}^{t}}$ and basic demand $\mathbf{f_{cd}^{t}}$ are estimated separately as Eqs. 3.114 -115, and other final demand $\mathbf{f_{others}^{t}}$ ('other' refers to demand apart from basic demand, namely, remaining needs for households, government, capital and exportation) is calculated through Eq. 3.116-119.

$$\mathbf{f_{rec}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times (\mathbf{f_{ID}}./\mathbf{x_{d}}) \quad (t \geq 1) \quad (3.114)$$

$$\mathbf{f_{cd}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times (\mathbf{f_{cd}}./\mathbf{x_{d}}) \quad (t \geq 1) \quad (3.115)$$

$$\mathbf{f_{hh}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times [\mathbf{f_{hh}^{0}}./(\mathbf{x_{d}} - \mathbf{f_{cd}^{t}} - \textstyle\sum_{k=1}^{t} \mathbf{f_{rec}^{\mathit{k}}})] \quad (t \geq 1) \quad (3.116)$$

$$\mathbf{f_{gov}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times [\mathbf{f_{gov}^{0}}./(\mathbf{x_{d}} - \mathbf{f_{cd}^{t}} - \textstyle\sum_{k=1}^{t} \mathbf{f_{rec}^{\mathit{k}}})] \quad (t \geq 1) \quad (3.117)$$

$$\mathbf{f_{cap}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times [\mathbf{f_{cap}^{0}}./(\mathbf{x_{d}} - \mathbf{f_{cd}^{t}} - \textstyle\sum_{k=1}^{t} \mathbf{f_{rec}^{\mathit{k}}})] \quad (t \geq 1) \quad (3.118)$$

$$\mathbf{f_{exp}^{t}} = \left(\mathbf{x^{t}} + \mathbf{y_{imp}^{t}} - \mathbf{Ax^{0}}\right) \times [\mathbf{f_{exp}^{0}}./(\mathbf{x_{d}} - \mathbf{f_{cd}^{t}} - \textstyle\sum_{k=1}^{t} \mathbf{f_{rec}^{\mathit{k}}})] \quad (t \geq 1) \quad (3.119)$$

…

Until $\mathbf{f_{rec}} + \mathbf{f_{cd}^{t}} + \mathbf{f_{hh}^{t}} + \mathbf{f_{gov}^{t}} + \mathbf{f_{cap}^{t}} + \mathbf{f_{exp}^{t}} = \mathbf{f_{d}}$ (3.71), and $\mathbf{x^{t}} = \mathbf{Ax^{t}} + \mathbf{f^{0}}$ (3.62).

End.

3.2.2.6 Total Flood Footprint

When the economic imbalances return to the pre-disaster situation, all the recovery period is complete. At this time, t denotes the time required to economic recovery, and the gap between the total production under pre-disaster level and the total required production of each round during the recovery process is the indirect economic loss of this disaster event (Eq.3.120); in other words, it is the amount of indirect impact ($x_{indirect}$; Figure 3.3). The total flood footprint (x_{total}) is the sum of the direct (x_{direct}) and indirect economic impacts (Eq.3.121). Many other results can be obtained from this model, such as how the destroyed capital is recovered step-by-step or how the labour affects the local economy.

$$x_{indirect} = sum\left(t\mathbf{x^{0}} - \left(\textstyle\sum_{k=1}^{t} \mathbf{x}^{k} + \sum_{k=1}^{t} \mathbf{y_{imp}^{\mathit{k}}}\right)\right) \quad (t \geq 1) \quad (3.120)$$

$$x_{total} = x_{direct} + x_{indirect} \quad (3.121)$$

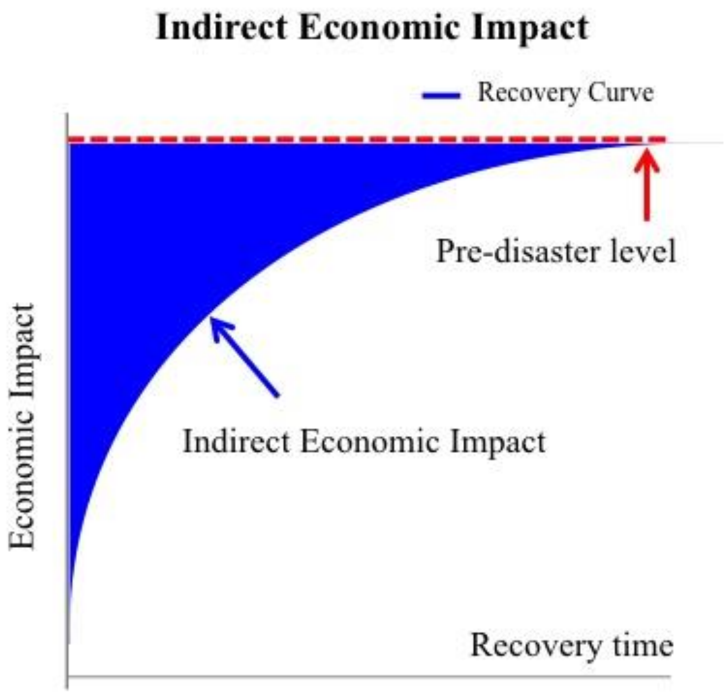


Figure 3.3. Indirect economic impact (for illustration purpose only).

3.2.3. Model Variables for Two-flood Event

The methodology of flood footprint assessment for multiple natural hazards is an improvement of the methodology that focuses on a single natural disaster event, as described previously. In this thesis, multiple natural disasters refers to a situation in which more than one disaster event occurs within the same economic system and when the second or the third event occurs, the economic system is still recovering from the previous natural disaster event. The basic theory and functions of this approach are still the same as described in Section 4.2.1 and the final goal of the recovery is to reach the economic conditions that existed before the first disaster. In other words, multiple natural disasters can be treated as a 'big' disaster, different from a single continuous event, such as a 'big' disaster that contains more than one shock, and then, the recovery process displays a dynamic trend. Hence, model variables also suffer many shocks, particularly in terms of capital and labour constraints.

Either for single disaster or multiple disasters, the basic supply bottleneck (Chapter 3.2.2.4) and rationing scheme (Chapter 3.2.2.5) are the same during the whole recovery process. The supply bottleneck is limited by both capital and labour constraints at each stage, and the rationing scheme is that intermediate demand and the basic demand are the priority satisfied, followed by recovery demands and other consumption demands. Here, some assumptions are made as follows. 1) It is assumed that import production and services in the pre-disaster economic system can be substituted with domestic production and services. 2) The amount of original imports and industrial production are assumed as being the maximum capacity of import and industrial production, respectively. 3) The detailed import at each stage is closely related to the sector of transportations system. 4) The supply bottleneck and rationing scheme for multiple disasters are still the same as for a single disaster (as described in Chapter 3.2.2.4 and 3.2.2.5) in the Flood Footprint Model. The approach that considers two disasters is taken as an example here, and the methodology for three or more natural hazards can be improved in the same way.

According to the various timeframes of the subsequent natural disasters, there are four types of economic system recovery conditions (Table 3.4). When the following disaster shocks the economic system, the damage resulting from the first kind of natural disaster can be:

1) both damaged capital and affected labour productivity due to the first disaster are in recovery;

2) industrial capital is in the process of reconstruction and the labour has already completely recovered;

3) the recovery of capital has been completed and labour is in the process of being rebuilt;

4) both capital and labour are fully recovered.

With consideration of the impact that induced by the following natural disaster, the estimation methods of capital and labour constraints caused by the four types of the subsequent natural hazard on the affected economic system are introduced below.

Table 3.4. Four types of the two natural disaster recovery.

Occurrence conditions of the subsequent natural disasters	Recovery conditions for previous natural disaster	
	Capital recovery	Labour recovery

Type 1	Recovering	Recovering
Type 2	Recovering	Completely recovered
Type 3	Completely recovered	Recovering
Type 4	Completely recovered	Completely recovered

3.2.3.1 Recovery Demand

This study assumes *m* stands for the time that the subsequent natural disaster shock the economic system. Since *m* is a specific time, it equals to the time gap between these two disasters ($1 \le m \le t$), the unit of m is as same as t[10], such as week, month or year period.

If the subsequent event does not occur, according to Eq.3.102, the remaining recovery demand ($\mathbf{f}^{\mathbf{t}}_{\mathbf{rec\_rem}}$) for time (*m+1*) equals to

$$\mathbf{f}^{\mathbf{m+1}}_{\mathbf{rec\_rem}} = \mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{m} \mathbf{f}^{k}_{\mathbf{rec}} \;\; (m \ge 1) \quad (3.122)$$

Since attendance of the following natural disaster raises the capital recovery demand in the following stage, the increased capital recovery demand of the subsequent event ($\mathbf{f}^{\mathbf{0}}_{\mathbf{rec2}}$) is required to taken into account. Therefore, the remaining recovery demand of the time (*m+1*) is increased as Eq.3.123.

$$\mathbf{f}^{\mathbf{m+1}}_{\mathbf{rec\_rem}} = \left(\mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{m} \mathbf{f}^{k}_{\mathbf{rec}}\right) + \mathbf{f}^{\mathbf{0}}_{\mathbf{rec2}} \;\; (m \ge 1) \quad (3.123)$$

In addition, from the time (*m+1*), in the Flood Footprint Model, the Eq.3.102 that refers to estimation of recovered capital in each round becomes Eq.3.124, and the damage fraction for next round (Eq.3.104) become Eq.3.125.

$$\mathbf{f}^{\mathbf{t}}_{\mathbf{rec}} = \min\left(\left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}^{\mathbf{0}}_{\mathbf{rec2}}\right) - \sum_{k=1}^{t-1} \mathbf{f}^{k}_{\mathbf{rec}}, \mathbf{f}^{\mathbf{t}}_{\mathbf{rem}}\right) \;\; (t \ge 1) \quad (3.124)$$

10 ‘t’ here means the time period t, when t=m, it means the time for the subsequent natural disaster occurs.

$$\boldsymbol{\alpha}_2{}^{\mathbf{t+1}} = \left(\left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}}\right) - \sum_{k=1}^{t} \mathbf{f}_{\mathbf{rec}}^{k}\right)./\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} \ \ (t \geq 1) \quad (3.125)$$

While in Scenario 2.1, the Eq.3.108 and Eq.3.110 are changing as Eq. 3.126 and 3.127.

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{t}} = \min\left(\left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}}\right) - \sum_{k=1}^{t-1} \mathbf{f}_{\mathbf{rec}}^{k}, \mathbf{f}_{\mathbf{new}}^{\mathbf{t}}\ \right) \ (t \geq 1) \quad (3.126)$$

$$\boldsymbol{\alpha}_2{}^{\mathbf{t+1}} = \left(\left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}}\right) - \sum_{k=1}^{t} \mathbf{f}_{\mathbf{rec}}^{k}\right)./\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} \ \ (t \geq 1) \quad (3.127)$$

3.2.3.2 Capital Limitations

The main influence of the following natural disaster on the capital parameter is reducing industrial capital production by increasing the capital damage fraction ($\alpha_2{}^0$). Under the conditions of Type 1 and 2, the capital loss from previous shock is in recovering stage, and when t=m, the damage fraction of capital (α^{m+1}) becomes

$$\boldsymbol{\alpha}_2{}^{m+1} = \boldsymbol{\alpha}_1{}^{m+1} + \boldsymbol{\alpha}_2{}^{0} \ (m \geq 1) \quad (3.128)$$

where $\boldsymbol{\alpha}_2^{\mathbf{m+1}}$ is industrial capital damage fractions at time $m+1$; $\boldsymbol{\alpha}_1^{\mathbf{m+1}}$ is the capital damage fractions that calculated from last round by Eq.3.125 or Eq.3.127; $\boldsymbol{\alpha}_2^{\mathbf{0}}$ is the direct capital damage fractions caused by the subsequent disaster. When t=m, the result of Eq.3.128 equals to the damage fraction that calculated by Eq.3.125 or Eq.3.127. These equations explain the impact on capital productivity resulted from the subsequent disaster from different views. The former one provides a logical explanation to show how the following damage part directly influence the total capital recovery; while Eq. 3.125 or 3.127 clarify it through mathematical ways. It means that just in the time m, Eq.3.128 can be used to calculate the damage fractions for time ($m+1$), and in the following stages, the calculation methods for the destroyed capital are according to Eq.3.125 or Eq.3.127.

For Type 3 and 4, the destroyed capital resulted from previous hazard has already fully recovered. Hence, from the capital perspective, the following disaster with these two types can be treated as a single shock event to the economic system. Eq.128 can be directly changed as

$$\boldsymbol{\alpha_2}^{m+1} = \boldsymbol{\alpha_2}^{0}\ (m \geq 1) \quad (3.129)$$

Meanwhile, estimations of industrial production limited by capital damage in the whole period from period m+1 becomes

$$\mathbf{x}_{\mathbf{cap}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_2}^{t}\right)\mathbf{x}^{\mathbf{0}}\ (\mathrm{t} > m \geq 1) \quad (3.130)$$

3.2.3.3 Labour Constraints

Eqs.3.66-3.69 from Chapter 3.2.2.2 shows the approach to estimate the labour constraints in the Flood Footprint Model. If the following disaster disrupts the recovery process of the labour productivity that affected by the former shock like Type 1 and 3, the damaged fractions of labour productivity caused by the subsequent event ($\boldsymbol{\beta}_2^{\mathbf{0}}$) should be added in the round (*m+1*) as Eq. 3.131. If the labour productivity finished recovery when the subsequent natural disaster occurs like Type 2 and 4, then the methods for assessing the following disaster impact on labour productivity are simplified as Eq.3.132.

$$\boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{m+1}} = \boldsymbol{\beta}_{\mathbf{1}}^{\mathbf{m+1}} + \boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{0}}\ (m \geq 1) \quad (3.131)$$

$$\boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{m+1}} = \boldsymbol{\beta}_{\mathbf{2}}^{\mathbf{0}}\ (m \geq 1) \quad (3.132)$$

where $\boldsymbol{\beta}_2^{\mathbf{m+1}}$ is industrial labour damage fractions at time *m+1*; $\boldsymbol{\beta}_1^{\mathbf{m+1}}$ is the labour damage fractions at time *m* if the subsequent disaster influence is not taken into account. Since *m* is a specific time and recovery scheme of labour productivity is an exogenous factor, Eqs.3.131 or 3.132 is only used to provide the labour affected fraction of the time (*m+1*).

The industrial production limited by labour constraints during next stages are measured as Eq.3.133.

$$\mathbf{x}_{\mathbf{lab}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta}_{\mathbf{1}}}^{t}\right)\mathbf{x}^{\mathbf{0}} \quad (t>m\geq 1) \quad (3.133)$$

3.2.3.4 Import

Since amount of imports depends significantly on the capital condition of transport sector, increased capital damaged fraction of transport sector due to the subsequent disaster ($\alpha^{0}{}_{tran2}$) lead to reduction of import capacity. As described in Chapter 3.2.2.5, Eq.3.134 and Eqs.3.125 or 3.127 provides the estimation of damage fraction of transport capital in time (*m+1*); and for next stages, the methods are still based on Eq.3.125 or Eq.3.127. At the same time, the measurement for import is as same as Eq.3.135.

$$\alpha_{2\_tran}^{m+1} = \alpha_{2\_tran}^{m+1} + \alpha_{2\_tran2}^{0} \; (m \geq 1) \quad (3.134)$$

$$\mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} = (1 - \alpha_{2\_tran}^{t})\mathbf{y}_{\mathbf{imp}}^{\mathbf{0}} \quad (\mathrm{t} > m \geq 1) \quad (3.135)$$

3.2.3.5 Rationing Scheme

The basic framework of rationing scheme is same as that in single natural disaster recovery (Chapter 3.2.2.5). Since the economic system suffered more damaged on capital, the conditions of two specific scenarios (scenarios 2.1 and 2.2) are improved by adding the increased recovery demand of the subsequent disaster into the total recovery demand. As results, Eq.3.79 and 3.105 are changed as Eq.3.136 and 3.137, respectively.

$$\mathbf{Ax^0}+\mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} < x^{\mathbf{t}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} \leq \mathbf{Ax^0}+\mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} + \left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}} - \textstyle\sum_{k=1}^{t-1}\mathbf{f}_{\mathbf{rec}}^{k}\right) \; (t \geq 1) \quad (3.136)$$

$$\mathbf{x}^{\mathbf{t}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{t}} > \mathbf{Ax^0}+\mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} + (\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}}) \quad (3.137)$$

3.2.3.6 Total Flood Footprint

Although some methods and equations in recovery process for multiple natural disasters are different with the approach mentioned in single natural disaster assessment, such as the estimations for damage fraction of capital (α), the basic theory framework and rationing scheme of the Flood Footprint Model are same. The estimations of flood footprint for multiple shocks are same as Eqs.3.120-121. Due to the different influences of the following natural hazards, total indirect flood footprint of economic system may show dynamic trends as in Figure 3.4.

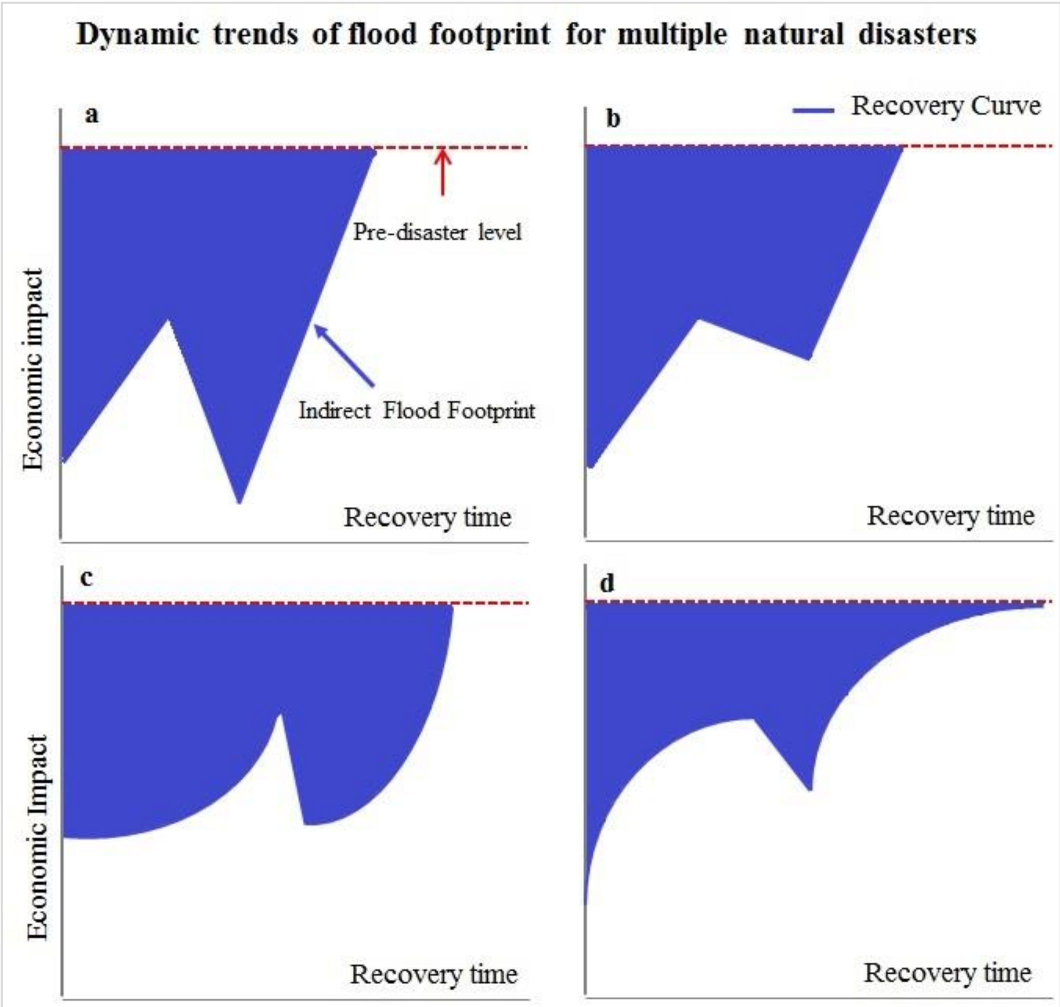


Figure 3.4. Examples of indirect flood footprint trends for multiple natural disasters.

Chapter 4 Flood Footprint Model Illustration I: A Hypothetical Single-flood Event

This chapter applies the Flood Footprint Model to a hypothetical single-flood case to illustrate the modelling process for an individual flood event. Meanwhile, an extensive sensitivity analysis of the flood footprint is discussed in this chapter, in particular, labour and capital recovery paths, and delayed recovery scenarios due to various factors such as poor or incompetent governance. This chapter seeks to guide practitioners and stakeholders in single-flood risk management by developing the modelling process step-by-step.

4.1. Introduction

The Flood Footprint Model can reflect the changes of product flows between industries during the disaster period and estimate the influence of capital damage and labour constraints caused by a flood event on the affected regional economy. The basic IO data of a hypothetical example is shown in Table 4.1 and it is retrieved from Miller and Blair (2009). Suppose that the local economy has only three sectors (S1, S2 and S3) and that S3 refers to the transport sector. The capital stock of the three sectors is $\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} = \begin{bmatrix} 3500 \\ 5000 \\ 1500 \end{bmatrix}$. In addition, basic household demand for the basic human needs of each sector is fixed in every period at $\mathbf{f}_{\mathbf{cd}}^{\mathbf{0}} = \mathbf{f}_{\mathbf{cd}}^{\mathbf{1}} = \cdots = \mathbf{f}_{\mathbf{cd}}^{\mathbf{t}} = \begin{bmatrix} 50 \\ 300 \\ 100 \end{bmatrix}$. It assumes that the time unit in this case is week.

As shown in Table 4.1, the total output of the three sectors $\mathbf{x}^{\mathbf{0}} = \begin{bmatrix} 1000 \\ 2000 \\ 1000 \end{bmatrix}$, the final demand $\mathbf{f}^{\mathbf{0}} = \begin{bmatrix} 300 \\ 1300 \\ 150 \end{bmatrix}$, and domestic coefficient $\mathbf{A} = \begin{bmatrix} 0.15 & 0.25 & 0.05 \\ 0.2 & 0.05 & 0.4 \\ 0.3 & 0.25 & 0.05 \end{bmatrix}$ (the calculation of **A** is referred to Eq.3.1).

Table 4.1. Flows for hypothetical example (3×3).

From \ To	S1	S2	S3	Final Demand (f^0): Basic demand (f_{cd})	Other demand (f_{others})	Total	Total Output (x)
S1	150	500	50	50	250	300	1000
S2	200	100	400	300	1000	1300	2000
S3	300	500	50	100	50	150	1000
Value-added	325	800	300		400		2150
Import	25	100	200				
Total Input	1000	2000	1000	350	1700		6150

Once a flood event occurs, the fraction of damaged industrial capital in each sector is assumed to be $\boldsymbol{\alpha_1} = \begin{bmatrix} 0.4 \\ 0.5 \\ 0.3 \end{bmatrix}$, while the percentage of reduced labour time loss $\boldsymbol{\beta_1} = \begin{bmatrix} 0.5 \\ 0.4 \\ 0.2 \end{bmatrix}$. In addition, it is also assumed that the labour productivity of all the three sectors are fully recovered during first four weeks, and the recovery trends for sector 1 and 2 are non-linear lines, while sector 3 is a linear line (Table 4.2).

Table 4.2. Percentages of labour time loss of three sectors caused by the flood event.

	S1	S2	S3
Week 1	50%	40%	20%
Week 2	20%	20%	10%
Week 3	5%	5%	0%
Week 4	0%	0%	0%

4.2. Application of Flood Footprint Model

Then, the recovery demand is

$$\mathbf{f_{ID}} = \widehat{\boldsymbol{\alpha_1}} \times \mathbf{s^0_{cap}} = \begin{bmatrix} 0.4 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.3 \end{bmatrix} \times \begin{bmatrix} 3500 \\ 5000 \\ 1500 \end{bmatrix} = \begin{bmatrix} 1400 \\ 2500 \\ 450 \end{bmatrix} \quad (4.1)$$

$$\mathbf{f_{HD}} = 0 \quad (4.2)$$

$$\mathbf{f_{rec}} = \mathbf{f_{ID}} + \mathbf{f_{HD}} = \begin{bmatrix} 1400 \\ 2500 \\ 450 \end{bmatrix} \quad (3.70);$$

The total required final demand is

$$\mathbf{f_d} = \mathbf{f^0} + \mathbf{f_{rec}} = \begin{bmatrix} 300 \\ 1300 \\ 150 \end{bmatrix} + \begin{bmatrix} 1400 \\ 2500 \\ 450 \end{bmatrix} = \begin{bmatrix} 1700 \\ 3800 \\ 600 \end{bmatrix} \quad (4.3);$$

The total required industrial output is

$$\mathbf{x_d} = \mathbf{A}\mathbf{x_d} + \mathbf{f_d} \quad (3.72)$$

$$\mathbf{x_d} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f_d} = \left(\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.15 & 0.25 & 0.05 \\ 0.2 & 0.05 & 0.4 \\ 0.3 & 0.25 & 0.05 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1700 \\ 3800 \\ 600 \end{bmatrix} = \begin{bmatrix} 4087 \\ 6376 \\ 3600 \end{bmatrix} (4.4);$$

According to Eqs. 10 and 11, the available production that is limited by capital damage is

$$\mathbf{x^1_{cap}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_1}^1\right)\mathbf{x^0} = \left(\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.4 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.3 \end{bmatrix} \right) \begin{bmatrix} 1000 \\ 2000 \\ 1000 \end{bmatrix} = \begin{bmatrix} 600 \\ 1000 \\ 700 \end{bmatrix} \quad (3.73).$$

The available production that is limited by labour constraints is

$$\mathbf{x^1_{lab}} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta}_1}^1\right)\mathbf{x^0} = \left(\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.4 & 0 \\ 0 & 0 & 0.2 \end{bmatrix} \right) \begin{bmatrix} 1000 \\ 2000 \\ 1000 \end{bmatrix} = \begin{bmatrix} 500 \\ 1200 \\ 800 \end{bmatrix} \quad (3.74).$$

The actual production after the shock is

$$\mathbf{x^1} = \min(\mathbf{x^1_{cap}}, \mathbf{x^1_{lab}}) = \min\left(\begin{bmatrix} 600 \\ 1000 \\ 700 \end{bmatrix}, \begin{bmatrix} 500 \\ 1200 \\ 800 \end{bmatrix} \right) = \begin{bmatrix} 500 \\ 1000 \\ 700 \end{bmatrix} \quad (3.75).$$

Because the available production is smaller than the required total production ($\mathbf{x^1} < x_{\mathbf{d}}$), the remaining industrial production cannot satisfy industrial requirements and final demands at the same time; such limited production results in a supply bottleneck. Import should be added as industrial input to support basic demand and recovery demand.

If import under the normal transport condition is supposed as $\mathbf{y}_{\mathbf{imp}}^{\mathbf{0}} = [25 \quad 100 \quad 200]$, then imports after the shock becomes

$$\mathbf{y}_{\mathbf{imp}}^{\mathbf{1}} = (1 - \alpha_{1\_S3}^{1})\mathbf{y}_{\mathbf{imp}}^{\mathbf{0}} = (1 - 0.3)[25 \quad 100 \quad 200] = [18 \quad 70 \quad 140] \quad (3.76).$$

At this time,

$$\begin{cases} \mathbf{x}^{1} + (\mathbf{y}_{\mathbf{imp}}^{\mathbf{1}})' = \begin{bmatrix} 500 \\ 1000 \\ 700 \end{bmatrix} + \begin{bmatrix} 18 \\ 70 \\ 140 \end{bmatrix} = \begin{bmatrix} 518 \\ 1070 \\ 840 \end{bmatrix} \\ \mathbf{A}\mathbf{x}^{\mathbf{0}} = \begin{bmatrix} 0.15 & 0.25 & 0.05 \\ 0.2 & 0.05 & 0.4 \\ 0.3 & 0.25 & 0.05 \end{bmatrix} \begin{bmatrix} 1000 \\ 2000 \\ 1000 \end{bmatrix} = \begin{bmatrix} 700 \\ 700 \\ 850 \end{bmatrix} \end{cases} \quad (4.5),$$
$$\downarrow$$
$$\mathbf{x}^{1} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{1}} < \mathbf{A}\mathbf{x}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{1}}$$

We now turn to scenario 1.

In Week 1

The available production, which includes imports, is $\mathbf{x}_{\mathbf{rem}}^{\mathbf{1}} = \begin{bmatrix} 518 \\ 1070 \\ 840 \end{bmatrix}$.

The actual final demand under the new economic balance is

$$\mathbf{x}_{\mathbf{rem}}^{\mathbf{1}} = \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{1}} + \mathbf{f}^{\mathbf{1}} \quad \rightarrow \mathbf{f}^{\mathbf{1}} = \mathbf{x}_{\mathbf{rem}}^{\mathbf{1}} - \mathbf{A}\mathbf{x}_{\mathbf{rem}}^{\mathbf{1}} = \begin{bmatrix} 518 \\ 1070 \\ 840 \end{bmatrix} -$$
$$\begin{bmatrix} 0.15 & 0.25 & 0.05 \\ 0.2 & 0.05 & 0.4 \\ 0.3 & 0.25 & 0.05 \end{bmatrix} \begin{bmatrix} 518 \\ 1070 \\ 840 \end{bmatrix} = \begin{bmatrix} 130 \\ 577 \\ 375 \end{bmatrix} \quad (4.6)$$

To repair the industrial capital damage, the rest of final demand ($\mathbf{f}_{\mathbf{rem}}^{\mathbf{1}}$) which excludes the basic demand of Week 1, is used first for industrial capital restoring ($\mathbf{f}_{\mathbf{rec}}^{\mathbf{1}}$) and then for other final demands ($\mathbf{f}_{\mathbf{others}}^{\mathbf{1}}$), such as government demand.

$$\mathbf{f}_{\mathbf{rem}}^{\mathbf{1}} = \mathbf{f}^{\mathbf{1}} - \mathbf{f}_{\mathbf{cd}}^{\mathbf{1}} = \begin{bmatrix} 130 \\ 577 \\ 375 \end{bmatrix} - \begin{bmatrix} 50 \\ 300 \\ 100 \end{bmatrix} = \begin{bmatrix} 80 \\ 277 \\ 275 \end{bmatrix} \quad (3.82)$$

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{1}} = \min(\mathbf{f}_{\mathbf{rec}}, \mathbf{f}_{\mathbf{rem}}^{\mathbf{1}}) = \min\left(\begin{bmatrix} 1400 \\ 2500 \\ 450 \end{bmatrix}, \begin{bmatrix} 80 \\ 277 \\ 275 \end{bmatrix}\right) = \begin{bmatrix} 80 \\ 277 \\ 275 \end{bmatrix} \quad (3.83)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{1}} = \mathbf{f}_{\mathbf{rem}}^{\mathbf{1}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{1}} = \begin{bmatrix} 80 \\ 277 \\ 275 \end{bmatrix} - \begin{bmatrix} 80 \\ 277 \\ 275 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad (3.84)$$

If the industrial capital of one sector has already regained pre-disaster levels, the damage fraction of this sector will become 0. When the damage fractions of all sectors are 0, industrial capital has been recovered. The damage fraction in Week 2 is calculated from Eq.3.85, which is introduced in Chapter 3.

$$\boldsymbol{\alpha_1}^{\mathbf{2}} = (\mathbf{f_{rec}} - \mathbf{f_{rec}^1})./\mathbf{s_{cap}^0} = \left(\begin{bmatrix}1400\\2500\\450\end{bmatrix} - \begin{bmatrix}80\\277\\275\end{bmatrix}\right)./\begin{bmatrix}3500\\5000\\1500\end{bmatrix} = \begin{bmatrix}0.38\\0.44\\0.12\end{bmatrix} \quad (3.85)$$

In Week 2,

$$\mathbf{x_{cap}^2} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha_1}^{\mathbf{2}}}\right)\mathbf{x^0} = \left(\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix} - \begin{bmatrix}0.38 & 0 & 0\\0 & 0.44 & 0\\0 & 0 & 0.12\end{bmatrix}\right)\begin{bmatrix}1000\\2000\\1000\end{bmatrix} = \begin{bmatrix}623\\1111\\884\end{bmatrix} \quad (3.86)$$

$$\mathbf{x_{lab}^2} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta_1}^{\mathbf{2}}}\right)\mathbf{x^0} = \left(\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix} - \begin{bmatrix}0.2 & 0 & 0\\0 & 0.2 & 0\\0 & 0 & 0.1\end{bmatrix}\right)\begin{bmatrix}1000\\2000\\1000\end{bmatrix} = \begin{bmatrix}800\\1600\\900\end{bmatrix} \quad (3.87)$$

$$\mathbf{x^2} = \min(\mathbf{x_{cap}^2}, \mathbf{x_{lab}^2}) = \begin{bmatrix}623\\1111\\884\end{bmatrix} \quad (3.88)$$

$$\mathbf{y_{imp}^2} = \left(1 - \alpha_{1\_S3}^2\right)\left(\mathbf{y_{imp}^0}\right)' = (1 - 0.12)[25 \quad 100 \quad 200] = [22 \quad 88 \quad 177] \quad (3.89)$$

$$\mathbf{x_{rem}^2} = \mathbf{x^2} + \left(\mathbf{y_{imp}^2}\right)' = \begin{bmatrix}645\\1199\\1060\end{bmatrix} \quad (4.7)$$

At this moment, the actual production of sector 3 (1060) is larger than its maximum production capacity (1000), it means that the actual x_{rem}^2 is:

$$\mathbf{x_{rem}^2} = \min(\mathbf{x^2} + \left(\mathbf{y_{imp}^2}\right)', \mathbf{x^0} + \left(\mathbf{y_{imp}^0}\right)') = \begin{bmatrix}645\\1199\\1000\end{bmatrix} \quad (3.90)$$

$$\mathbf{x_{rem}^2} = \mathbf{A}\mathbf{x_{rem}^2} + \mathbf{f^2} \quad (3.91)$$

$$\mathbf{f^2} = \mathbf{x_{rem}^2} - \mathbf{A}\mathbf{x_{rem}^2} = \begin{bmatrix}645\\1199\\1000\end{bmatrix} - \begin{bmatrix}0.15 & 0.25 & 0.05\\0.2 & 0.05 & 0.4\\0.3 & 0.25 & 0.05\end{bmatrix}\begin{bmatrix}645\\1199\\1000\end{bmatrix} = \begin{bmatrix}199\\610\\457\end{bmatrix} \quad (3.92)$$

$$\mathbf{f_{rem}^2} = \mathbf{f^2} - \mathbf{f_{cd}^2} = \begin{bmatrix}199\\610\\457\end{bmatrix} - \begin{bmatrix}50\\300\\100\end{bmatrix} = \begin{bmatrix}149\\310\\357\end{bmatrix} \quad (3.93)$$

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{2}} = \min(\mathbf{f}_{\mathbf{rec}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{t}}, \mathbf{f}_{\mathbf{rem}}^{\mathbf{2}}) = \min\left(\begin{bmatrix}1320\\2223\\175\end{bmatrix}, \begin{bmatrix}149\\310\\357\end{bmatrix}\right) = \begin{bmatrix}149\\310\\175\end{bmatrix} \quad (3.94)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{2}} = \mathbf{f}_{\mathbf{rem}}^{\mathbf{2}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{2}} = \begin{bmatrix}149\\310\\357\end{bmatrix} - \begin{bmatrix}149\\310\\175\end{bmatrix} = \begin{bmatrix}0\\0\\182\end{bmatrix} \quad (3.95)$$

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{3}} = \left(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{2} \mathbf{f}_{\mathbf{rec}}^{k}\right)./\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} = \left(\begin{bmatrix}1400\\2500\\450\end{bmatrix} - \left(\begin{bmatrix}80\\277\\275\end{bmatrix} + \begin{bmatrix}149\\310\\175\end{bmatrix}\right)\right)./\begin{bmatrix}3500\\5000\\1500\end{bmatrix} = \begin{bmatrix}0.33\\0.38\\0\end{bmatrix}$$

(3.96)

……

In Week 5,

$$\begin{cases} \mathbf{x}^{\mathbf{5}} + \left(\mathbf{y}_{\mathbf{imp}}^{\mathbf{5}}\right)' = \begin{bmatrix}776\\1741\\1000\end{bmatrix} \\ \mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{5}} = \begin{bmatrix}750\\1000\\950\end{bmatrix} \\ \mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{4} \mathbf{f}_{\mathbf{rec}}^{k} = \begin{bmatrix}871\\898\\0\end{bmatrix} \end{cases} \quad (4.8)$$

$$\downarrow$$
$$Scenario\ 2$$
$$\downarrow$$
$$\mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{5}} < x^{5} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{5}} \leq \mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{5}} + \left(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{4} \mathbf{f}_{\mathbf{rec}}^{k}\right)$$
$$\downarrow$$
$$Scemario\ 2.1$$

While

$$\mathbf{f}_{\mathbf{new}}^{\mathbf{5}} = \mathbf{x}^{\mathbf{5}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{5}} - \mathbf{Ax}^{\mathbf{0}} - \mathbf{f}_{\mathbf{cd}}^{\mathbf{5}} = \begin{bmatrix}26\\741\\50\end{bmatrix} \quad (4.9)$$

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{5}} = min\left(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{4} \mathbf{f}_{\mathbf{rec}}^{k}, \mathbf{f}_{\mathbf{new}}^{\mathbf{5}}\right) = \begin{bmatrix}26\\741\\0\end{bmatrix} \quad (4.10)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{5}} = \mathbf{f}_{\mathbf{new}}^{\mathbf{5}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{5}} = \begin{bmatrix}0\\0\\50\end{bmatrix} \quad (4.11)$$

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{6}} = \left(\mathbf{f}_{\mathbf{rec}} - \textstyle\sum_{k=1}^{5} \mathbf{f}_{\mathbf{rec}}^{k}\right)./\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} = \begin{bmatrix}0.24\\0.03\\0\end{bmatrix} \quad (4.12)$$

……

In Week 14,

$$\mathbf{f}_{\mathbf{new}}^{\mathbf{14}} = \mathbf{x}^{\mathbf{14}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{14}} - \mathbf{Ax}^{\mathbf{0}} - \mathbf{f}_{\mathbf{cd}}^{\mathbf{14}} = \begin{bmatrix} 252 \\ 1000 \\ 50 \end{bmatrix} \quad (4.13)$$

$$\mathbf{f}_{\mathbf{rec}}^{\mathbf{14}} = min\left(\mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{13} \mathbf{f}_{\mathbf{rec}}^{k}, \mathbf{f}_{\mathbf{new}}^{\mathbf{14}}\right) = \begin{bmatrix} 81 \\ 0 \\ 0 \end{bmatrix} \quad (4.14)$$

$$\mathbf{f}_{\mathbf{others}}^{\mathbf{14}} = \mathbf{f}_{\mathbf{new}}^{\mathbf{14}} - \mathbf{f}_{\mathbf{rec}}^{\mathbf{14}} = \begin{bmatrix} 171 \\ 1000 \\ 50 \end{bmatrix} (4.15)$$

$$\left\{\begin{array}{c} \mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{14} \mathbf{f}_{\mathbf{rec}}^{k} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ \boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{15}} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ \downarrow \\ \mathbf{x}^{\mathbf{15}} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{15}} > \mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{15}} + \left(\mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{14} \mathbf{f}_{\mathbf{rec}}^{k}\right) \quad (4.16) \\ \downarrow \\ Scenario\ 2.2 \end{array}\right.$$

In Week 15, $\mathbf{x}^{\mathbf{15}} = \mathbf{Ax}^{\mathbf{15}} + \mathbf{f}^{\mathbf{0}} = \begin{bmatrix} 1000 \\ 2000 \\ 1000 \end{bmatrix}$ (4.17), and the recovery period ends.

Thus, according to my algorithm[11], 14 weeks are needed for the local economic system to recover to the pre-disaster situation (detail calculation of Eqs.A1-10 see Appendix A).

The total indirect impact is estimated as

$$x_{indirect} = sum(14\mathbf{x}^{\mathbf{0}} - \sum_{k=1}^{14} \mathbf{x}^{k} + \sum_{k=1}^{14} \mathbf{y}_{\mathbf{imp}}^{k}) = 6182 \quad (4.18);$$

the total direct flood footprint is calculated as

$$x_{direct} = sum\left(\widehat{\boldsymbol{\alpha}_{\mathbf{1}}} \times \mathbf{s}_{\mathbf{cap}}^{\mathbf{0}}\right) = 4350 \quad (4.19);$$

and the total flood footprint of this hypothetical flooding is

[11] The results here are only according to the algorithm proposed in Chapter 3.2, not the practical recovery situation of the regional economic system.

$$x_{total} = x_{direct} + x_{indirect} = 10532 \quad (4.20).$$

Direct economic loss accounts for 41% of the total flood footprint, while indirect part represents 59%.

4.3. Sensitivity Analysis

The final economic consequences of a flood event are sensitive to input data and the parameters of the Flood Footprint Model. Due to a lack of empirical data to do model validation, different recovery scenarios should be taken into consideration. In this section, the condition of the hypothetical numerical example in Section 4.2 is assumed as the base scenario. A series of sensitivity analyses based on this scenario, such as alternative labour and capital recovery paths, various delayed recovery, basic demands and imports, are provided as below.

4.3.1. Alternative Labour Productivity Recovery

The recovery path of labour is an exogenous factor in the model and needs separate attention in each case. Although there is no real statistical data to show how labour is restored in each sector after a flooding event, in general, recovery labour plans often depend on the decisions of policy-makers and the different reality situations. In some cases, the productivity of labour is only affected by some specific factors, such as transportation systems. If the recovery scheme of this kind of factor is linear, then the labour recovery path will also follow the same trend. In section 4.2, the recovered parts of labour productivity in each stage are assumed as specific data (Table 4.2). However, apart from this plan, the recovery paths can also be organized as sets of continuous curves. That is to say, the percentage of available labour productivity (LP) of each sector at time t can be according to the different rules. To better analyse how a labour restoration plan may influence the recovery process, four new scenarios of labour productivity recovering paths have been selected (Table 4.3), Scenario L-1 shows linear curves, while Scenario L-2 and L-3 indicate non-linear paths, and L-4 is the mixed plan of both linear and non-linear trends. It should be noticed that only the labour restoring paths change among these four scenarios; other related factors are the same as those in Section

4.2; the recovery process of capital productivity can be different in each scenario because this factor is endogenous and no other capital restoration plan is considered here.

In Scenario L-1, the trends of labour productivity recovery (*LP*) of 3 sectors are assumed as linear curves (Eq. 4.20), and such *LP* is only related to labour parameter (*β*) in the Flood Footprint Model.

$$\begin{cases} LP_{s1} = 0.15t + 0.35 \\ LP_{s2} = 0.1t + 0.5 \\ LP_{s3} = 0.1t + 0.7 \end{cases} \quad (4.20).$$

and the available productivity of labour at each stage can be estimated as

$$\begin{cases} x_{lab\_S1}^{t} = (0.15t + 0.35)x^{0} \\ x_{lab\_S2}^{t} = (0.1t + 0.5)x^{0} \\ x_{lab\_S3}^{t} = (0.1t + 0.7)x^{0} \end{cases} \quad (4.21).$$

Scenario L-2 is polynomial trends, and the recovered labour productivity at the time t of 3 sectors are

$$\begin{cases} LP_{s1} = 0.02t^{2} - 0.014t + 0.52 \\ LP_{s2} = 0.01t^{2} + 0.01t + 0.58 \\ LP_{s3} = 0.01\,t^{2} + 0.01t + 0.8 \end{cases} \quad (4.22),$$

and the remaining labour production become

$$\begin{cases} x_{lab\_S1}^{t} = (0.02t^{2} - 0.014t + 0.52)x^{0} \\ x_{lab\_S2}^{t} = (0.01t^{2} + 0.01t + 0.58)x^{0} \\ x_{lab\_S3}^{t} = (0.01\,t^{2} + 0.01t + 0.8)x^{0} \end{cases} \quad (4.23).$$

Scenario L-3 reveals logarithmic trends,

$$\begin{cases} LP_{s1} = 0.33\ln(t) + 0.5 \\ LP_{s2} = 0.26\ln(t) + 0.6 \\ LP_{s3} = 0.13\ln(t) + 0.8 \end{cases} \quad (4.24),$$

and the recovered labour production are

$$\begin{cases} x_{lab\_S1}^{t} = [0.33\ln(t) + 0.5]x^{0} \\ x_{lab\_S2}^{t}[0.26\ln(t) + 0.6]x^{0} \\ x_{lab\_S3}^{t} = [0.13\ln(t) + 0.8]x^{0} \end{cases} \quad (4.25).$$

Scenario L-4 is the mixed situation,

$$\begin{cases} LP_{s1} = 0.02t^2 - 0.014t + 0.52 \\ LP_{s2} = 0.26\ln(t) + 0.6 \\ LP_{s3} = 0.1x + 0.7 \end{cases} \quad (4.26),$$

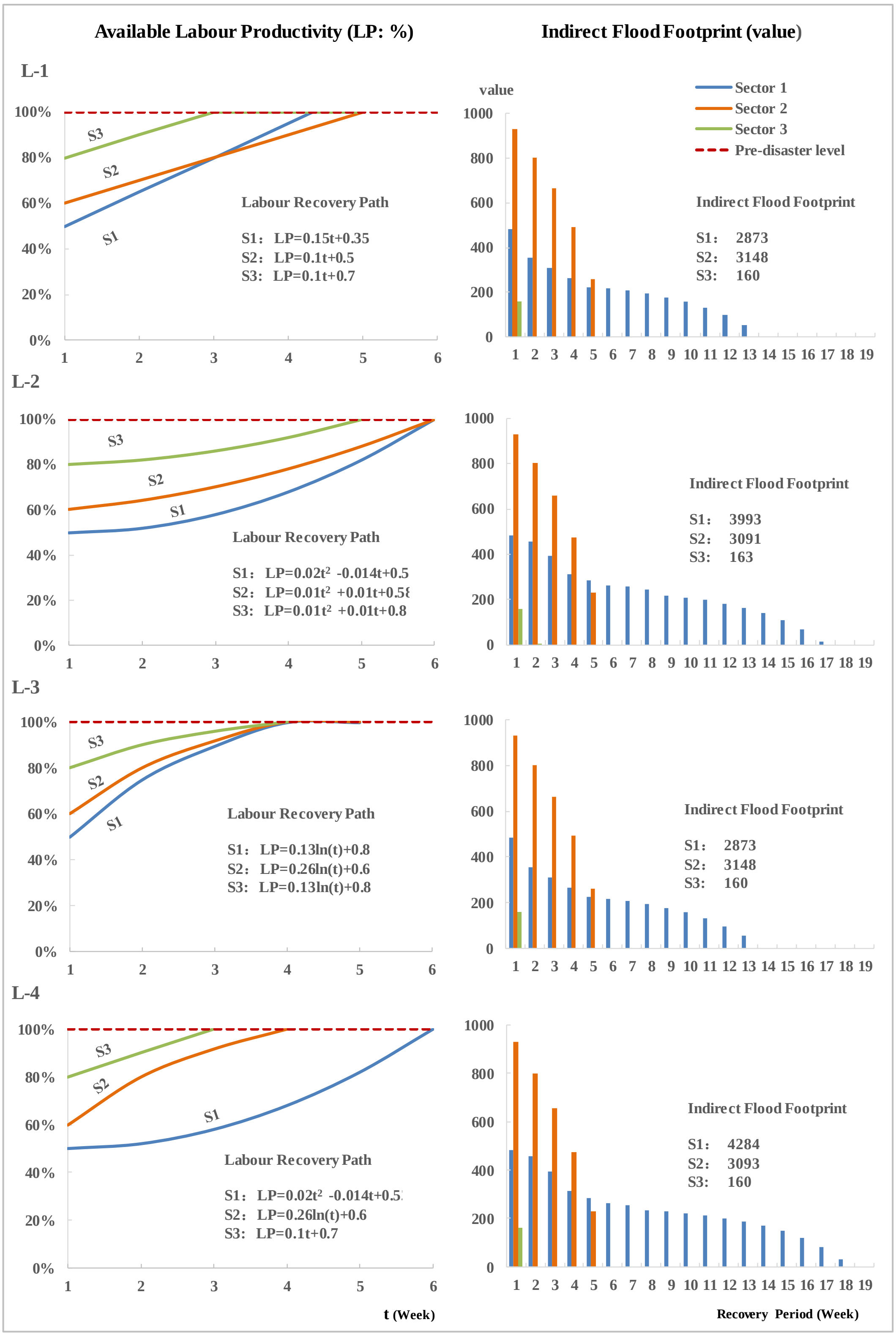
and Eq. 3.69 become

$$\begin{cases} x_{lab\_S1}^{t} = (0.02t^2 - 0.014t + 0.52)x^0 \\ x_{lab\_S2}^{t} = (0.01t^2 + 0.01t + 0.58)x^0 \\ x_{lab\_S3}^{t} = (0.01\ t^2 + 0.01t + 0.8)x^0 \end{cases} \quad (4.27).$$

Table 4.3. Results of labour productivity recovery scenarios.

Scenario	Recovery Path	Available Labour Productivity (LP)	Recovery Period	Indirect Flood Footprint	Total Flood Footprint
L-1	Linear	$\begin{cases} LP_{s1} = 0.15t + 0.35 \\ LP_{s2} = 0.1t + 0.5 \\ LP_{s3} = 0.1t + 0.7 \end{cases}$	14 Weeks	6182	10532
L-2	Polynomial	$\begin{cases} LP_{s1} = 0.02t^2 - 0.014t + 0 \\ LP_{s2} = 0.01t^2 + 0.01t + 0. \\ LP_{s3} = 0.01\ t^2 + 0.01t + 0 \end{cases}$	18 Weeks	7247	11598
L-3	Logarithmic	$\begin{cases} LP_{s1} = 0.33\ln(t) + 0.5 \\ LP_{s2} = 0.26\ln(t) + 0.6 \\ LP_{s3} = 0.13\ln(t) + 0.8 \end{cases}$	14 Weeks	6182	10532
L-4	Mixed plan	$\begin{cases} LP_{s1} = 0.02t^2 - 0.014t + 0 \\ LP_{s2} = 0.26\ln(t) + 0.6 \\ LP_{s3} = 0.1x + 0.7 \end{cases}$	19 Weeks	7537	11887

Among these four scenarios, L-2 and L-4 need a longer time to complete restoration and their indirect flood footprints are also higher than others (Figure 4.1). The labour restoration path has a significant impact on the final flood footprint of a flooding event. Meanwhile, L-1 and L-3 have the same indirect flood footprint. Such outcomes can be explained by their actual production, which depends on the minimum of labour and capital production. For L-1 and L-3, despite labour recovery conditions being different, they have the same capital production which is smaller than their labour production, leading to the same actual production in each stage. It is also helpful to explain why the indirect flood footprint of S2 in L-2 and L-4 are almost equal.



Notes: the horizontal axis shows the recovery period and the whole recovery process starts from the first week (the number of the horizontal axis is 1) after the disaster.

Figure 4.1. *Four types of labour productivity recovery curves and their indirect flood footprint. L-1 is the linear recovery curve, L-2, L-3 and L-4 are the non-linear curves.*

4.3.2. Alternative Capital Productivity Restoration

In spite of the capital productivity recovery scheme in the Flood Footprint Model being an endogenous element, it can also be recovered through a specified path according to different situations. As a matter of fact, some sectors have their own specific recovery plan, especially infrastructure sectors, such as the electricity sector and water supply sector. These sectors are not only key to the operation of other industries, but are also the basic guarantee for human life. Therefore, compared with other general sectors, such critical sectors are always recovered as priority industries. For example, in the 2016 Leeds flooding in the UK, the West Yorkshire Combined Authority's Investment Committee established a Business Flood Recovery Fund to support businesses from priority sectors: manufacturing, food and drink, low carbon and environmental, financial and professional services, health and life sciences and digital and creative ('Combined Authority', 2016, January 20). Such actions allow priority sectors to be rebuilt earlier than other sectors. It implies that the damaged sectors are not recovered simultaneously during the process of the recovery.

Table 4.4 and Figure 4.2 display four scenarios to better illustrate how these situations influence the total restoration process of the affected economic system. Sector 2 is assumed as critical sector; the capital recovery scheme of sector 2 is different to the other two sectors among the scenarios below. In the Base Scenario, all of the 3 sectors recover from the same time—Week 1 (Section 4.2). Scenario C-1 assumes that only the capital restoration of Sector 2 is from Week 4; while in Scenario C-2, only Sector 2 is a priority sector, with restoration time occurring in Week 1 and others in Week 4. Scenario C-3 shows the different recovery times of each sector: Sector 1 from Week 6, Sector 2 from Week 4 and Sector 3 from Week 1.

According to the basic conditions of Scenario C-1, during the Week 1 to Week 3, the damage fractions of Sector 2 are

$$\alpha_{1\_s2}^{1} = \alpha_{1\_s2}^{2} = \alpha_{1\_s2}^{3} = \alpha_{1\_s2}^{4} = 0.5 \quad (4.28);$$

recovered capital of Sector 2 are

$$f_{rec\_S2}^{1} = f_{rec\_S2}^{2} = f_{rec\_S2}^{3} = 0 \quad (4.29).$$

Until in Week 4, Sector 2 starts recovering,

$$f^4_{rec\_S2} = \min\left(f_{rec\_s2} - \sum_{k=1}^{3} f^k_{rec\_s2}\,, f^4_{rem\_S2}\right) \text{ (4.30)}$$

$$\alpha^5_{1\_s2} = \left(f_{rec\_s2} - \sum_{k=1}^{4} f^k_{rec\_s2}\right)./s^0_{cap\_s2} \text{ (4.31).}$$

Scenario C-2 describes the situation that during the first three weeks, the damage ratio of Sector 1 are:

$$\alpha^1_{1\_s1} = \alpha^2_{1\_s1} = \alpha^3_{1\_s1} = \alpha^4_{1\_s2} = 0.4 \text{ (4.32)}$$

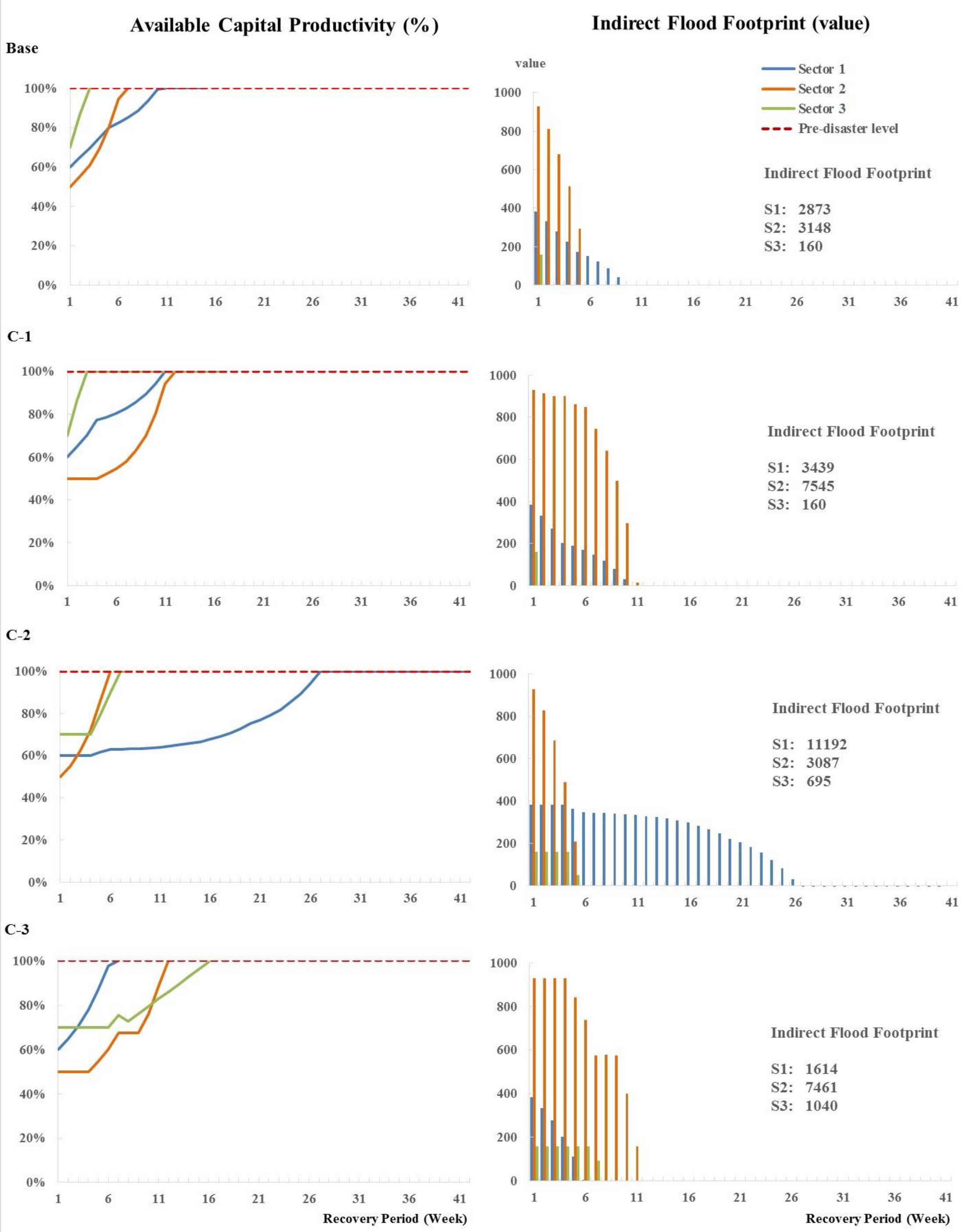
$$\alpha^1_{1\_s3} = \alpha^2_{1\_s3} = \alpha^3_{1\_s3} = \alpha^4_{1\_s3} = 0.3 \text{ (4.33)}$$

The recovered parts of these two sectors are 0. Until in Week 4, the production of Sector 1 and 3 can be allocated to recovery demand.

Table 4.4. Results of capital productivity recovery scenarios.

Scenario	Capital Recovery Path	Recovery Period	Indirect Flood footprint	Total Flood Footprint
Base	All the sectors from Week 1	14 Weeks	6182	10532
C-1	Only S2 from Week 4	16 Weeks	11144	15494
C-2	Only S2 from Week1, others from Week 4	41 Weeks	14974	19324
C-3	S2 from Week 4, S1 from Week 1, S3 from Week 6	15 Weeks	10116	14466

The outcomes under these four kinds of industrial capital restoration paths are totally different according to my estimation (Table 4.4). Scenario C-2 requires the longest recovery period (41 weeks) and has the largest total flood footprint (19324); its indirect flood footprint (14974) is almost 3 times larger than that of the Base Scenario. From the sector perspective, the largest indirect flood footprint of S1, S2 and S3 are shown in Scenario C-2, C-1 and C-3 (Figure 4.2) and such a situation can be explained as an accumulated effect. Taking S2 as an example, in the Scenario Base and C-2, the restoration of S2 is from the beginning stage; in other two scenarios, S2 remains damaged during the first three weeks without any recovery action. Hence, the accumulated economic loss results in a longer restoration period and larger flood footprint. Even with the extension of the recovery time of one sector, the recovery



Base scheme is the situation that all of the 3 sectors recovered from Week 1. Scenario C-1 assumes that only the capital recovery of S2 is from Week 4; while in Scenario C-2, only S2 is priority sector, which the recovery time is Week 1 and others from Week 4. Scenario C-3 shows the different recovery time of each sector, S1 from Week 1, S2 from Week 4 and S3 from Week 6.

Notes: the horizontal axis shows the recovery period and the whole recovery process starts from the first week (the number of the horizontal axis is 1) after the disaster.

Figure 4.2. Available capital productivity and indirect flood footprint of three sectors under four types of capital productivity recovery schemes.

time and economic loss of the whole economic system will become longer and higher, respectively. This example only focuses on 3 sectors; if such scenarios occurred in an economic system that includes 42 sectors, the final impact will be much larger.

4.3.3. Various Delayed Recovery

Delayed recovery examples exist in many real cases since post-disaster reconstruction is not usually performed immediately when the disaster occurs. Damaged physical infrastructure is a barrier to economic system restoration, as in the case of Haiti's recovery. Hurricane Matthew struck southwestern Haiti on 4th October 2016 and along the southern coast, 90% of houses were damaged and most of the crops destroyed. This storm caused \$1.89 billion loss and left about 1.4 million people (most were children and women) in need of humanitarian assistance (OCHA, 2016). Relief supplies could not be delivered to the affected area due to the damaged infrastructure and blocked roads, leading to more than 8 thousand people still lacking water and food one month later (ACTED, 2016). As a general rule, the priority work during the disaster period is rescue and relief work; the action of reconstruction will be conducted until the displaced people are resettled. Thus, rebuilding industrial production capacity has to start from a few weeks or months after a disaster.

Lack of financial assistance or incompetent governance is another reason for delays in recovery, like in the cases of Sint Maarten and Puerto Rico. Hurricane Irma crossed the island of Sint Maarten (a constituent island country of the Kingdom of the Netherlands) on 6th September 2017: up to 70% of the houses were badly damaged and thousands of residents were affected, with an estimated economic loss of nearly \$1.2 billion economic. But the government of Sint Maarten and Holland spent more than six weeks discussing issues of responsibilities, recovery plans and measures, especially for recovery funds (Sint Maarten Government, 2017, October 31). Lack of financial assistance was the immediate impact of extensive delays of the recovery work in Sint Maarten.

Another case is the restoration of Puerto Rico after Hurricane Maria. On 20th September 2017, Hurricane Maria landed on Puerto Rico with a strong storm surge and heavy rainfall; nearly the entire power grid, 95% of cell networks and 85% of above/ground phone and internet cables were destroyed, leaving millions of citizens without enough food, running water or electricity (Sanchez and Chavez, 2017, October 13). As estimated by Puerto Rico's governor, $94.4 billion was required to recover the damage (Associated Press, 2017, November 14). However, the US government refused to provide sufficient financial aid; additionally, the government of Puerto Rico itself accumulated over $70 billion in debt before this storm (Walsh, 2017, May 16), resulting in the slow process of the restoration in Puerto Rico. Two month later, people there still remained in the 'dark' with only 50% of power restored and some other areas maybe having to wait for at least six months (Galarza and Lee, 2017, November 19). With serious food shortages and less recovery funds, the biggest challenge for Puerto Rico is how to survive under such conditions, prolonging recovery time for the local economic system .

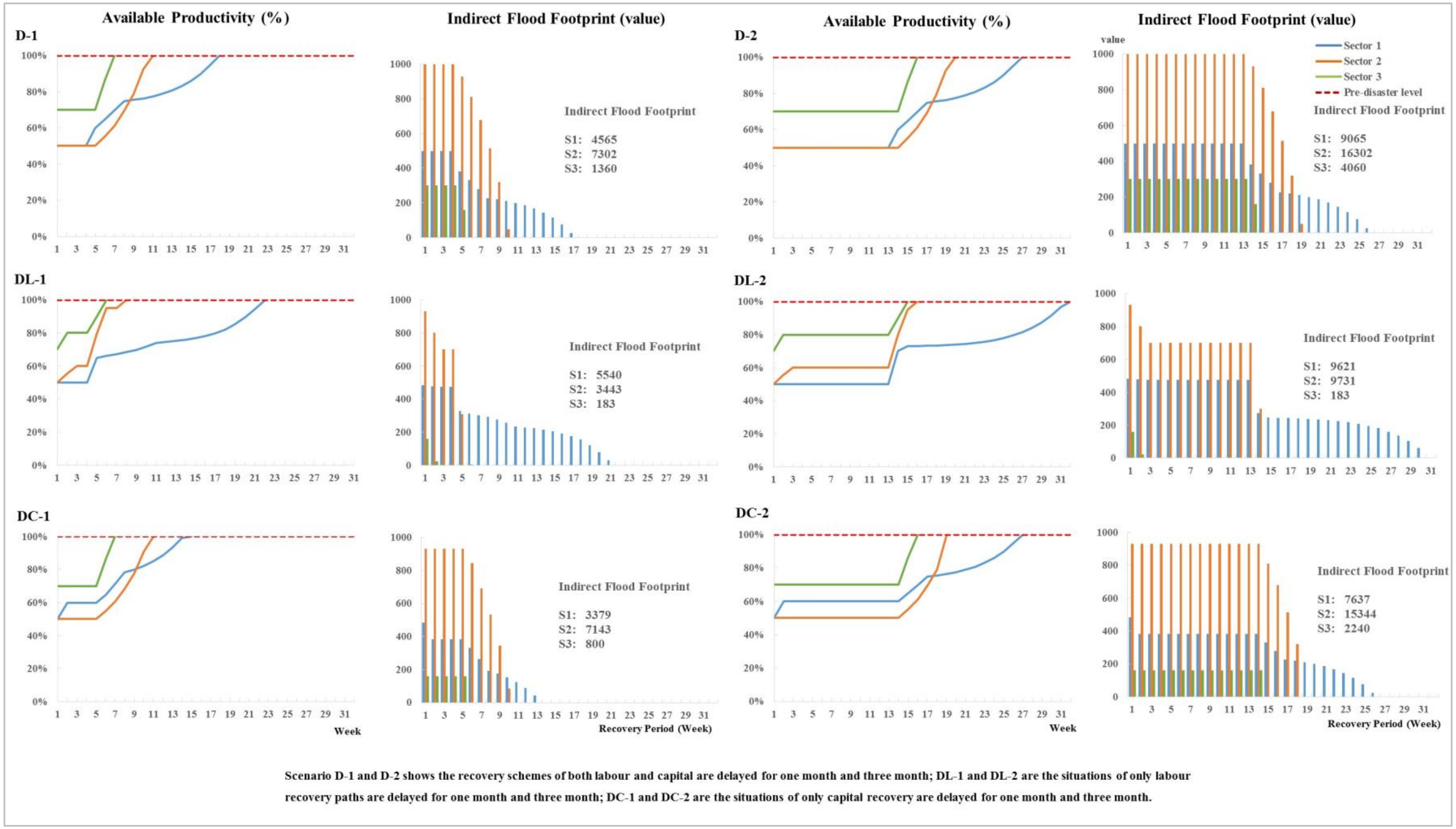
Table 4.5. Results of delayed recovery scenarios.

Scenario	Delay factor	Delay time	Recovery Period	Indirect Flood footprint	Total Flood Footprint
Base	None	No delay	14 Weeks	6182	10532
DL-1	Labour	One month	21 Weeks	9166	13516
DL-2	Labour	Three months[1]	31 Weeks	19535	23885
DC-1	Capital	One month	14 Weeks	11322	15672
DC-2	Capital	Three months	26 Weeks	25221	29571
D-1	Total[2]	One month	17 Weeks	13227	17578
D-2	Total	Three months	26 Weeks	29427	33777
D-3	Total	Six months	39 Weeks	52827	57177
D-4	Total	Twelve months	65 Weeks	99627	103977

1. Here one year has 52 weeks, sis months equal 26 weeks and three months has 13 weeks.
2. It should be noticed that, like the situation of D-1, imports as one kind of external support does not exist during the delay period of recovery.

Here, we tested differences in delay parameters and delay time of the hypothetical numerical example (Table 4.5). In Scenario DL-1 and DL-2, only labour restoration is considered as the delayed parameter; while DC-1 and DC-2 only focus on the capital recovery delay. For the other four scenarios D-1 to D-4, both the recovery of labour and capital are delayed for one, three, six and twelve months. The main effect of delayed recovery, regardless of whether the delay factor is labour or capital, or both of them, is to increase the flood footprint and extend the recovery period. Base Scenario refers to no delay condition and so has the smallest flood footprint and shortest recovery period; while D-4 has the longest recovery period (65 weeks), and the largest total flood footprint (103977), which is almost 10 times higher than in the Base Scenario. The indirect flood footprint (99627) in Scenario D-4 accounts for 96% of total flood footprint, which is nearly 22 times larger than the direct flood footprint (4350). The accumulated indirect economic impact during the delay period results in high cost when compared with the direct loss.

Figure 4.3 compares available productivity and indirect flood footprint of three sectors under six kinds of delay scenarios. When the delay time is one month, the flood footprint of Scenario D-1 is larger than that of DL-1 and DC-1; similarly, with a three-month delay, the total flood footprint of D-2 is also bigger than DL-2 and DC-2. It can be concluded that in this hypothetical numerical example, delays in both labour and capital recovery can create more economic loss than the conditions of the single parameter delay. There is one point that should be emphasized: available productivity is restricted by the minimum of capital and labour productivity. This is why in the first month in DL-1, even though there is no recovery for labour productivity, the available productivity of S2 and S3 are still increasing. The main limitation for the productivity of S2 and S3 in DL-1 is the capital factor, and for S1 it is the labour factor. The key constraint also explains the indirect flood footprint trends of 3 sectors during the delay time. Taking Scenario DL-1 as an example, in the labour delay period, S1 remains the same since its available production depends on labour; S2 decreases in the first two weeks and then stays the same because its production is mainly affected by capital in Weeks 1-2 and then turns to labour. S3 is in the same situation as S2: output of S3 is constrained by capital in Week 1 and then by labour. Two weeks for full recovery in S3 leads to the same indirect flood footprint results in Scenarios DL-1 and DL-2.



Scenario D-1 and D-2 shows the recovery schemes of both labour and capital are delayed for one month and three month; DL-1 and DL-2 are the situations of only labour recovery paths are delayed for one month and three month; DC-1 and DC-2 are the situations of only capital recovery are delayed for one month and three month.

Notes: the horizontal axis shows the recovery period and the whole recovery process starts from the first week (the number of the horizontal axis is 1) after the disaster.

Figure 4.3. *Available productivity and indirect flood footprint of three sectors under six delay scenarios.*

4.3.4. Sensitivity to the Critical Constraint Factor

Labour and capital, as the two main parameters in the model, have significant influences on the whole recovery process. The available capacity of industries in each recovery step is primarily constrained by these two factors. In real disaster cases, not all the flooding events impact on the labour or capital in the flood area. Also, not all industrial productivity in the affected sectors is limited by labour and capital at the same time. Sometimes, although both labour and capital for some specific sectors are influenced by a flood event, the productivity of this sector is only constrained by the labour or capital factor. For example, after the 2017 Hurricane Harvey, nearly 60% of contractors from the construction business reported the problem of skilled labour shortage (Grace Donnelly, 2017, September 18). High demand from commercial construction sectors and limited skilled labour led to a difficult recovery in the southern states and the Caribbean. Similarly, Hurricane Katrina hit New Orleans 11 years ago and caused nearly 54 billion USD damage, especially in the industries of gas and oil extraction, industrial chemical manufacturing and petroleum refining. The Federal Reserve Board of Governors reported that compared with the previous month, the production from the above industries was reduced by 1.7 percent in the disaster month, causing the disruptions of the hurricane (Timothy Boone, 2016, August 26; Kevin Kliesen, 2017, September 5). In other words, the production capacity of the energy sectors was seriously limited by the damaged capital in this event.

Based on the situation of the hypothetical numerical example, scenarios of sectors that either limited by labour or capital or both of them are compared below (Table 4.6). Scenario R-1 assumes that the production of Sector 1 during the recovery stage is only constrained by the labour, here the accessible production of the time *t* is

$$\begin{cases} {x_{S1}}^{t} = x_{lab\_S1}^{1}, \\ {x_{S2}}^{t} = \min(x_{cap\_S2}^{t}, x_{lab\_S2}^{t}) \\ {x_{S3}}^{t} = \min(x_{cap\_S3}^{t}, x_{lab\_S3}^{t}) \end{cases} \quad (4.34).$$

Scenario R-2 is the situation that the productivity of Sector 1 is only limited by the capital damage, here the actual production of the time t become

$$\begin{cases} {x_{S1}}^{t} = x_{cap\_S1}^{1}, \\ {x_{S2}}^{t} = \min(x_{cap\_S2}^{t}, x_{lab\_S2}^{t}) \\ {x_{S3}}^{t} = \min(x_{cap\_S3}^{t}, x_{lab\_S3}^{t}) \end{cases} \quad (4.35).$$

Scenario R-3 shows that the production of Sector 1 is only affected by the labour factor and Sector 2 is only influenced by industrial damaged capital, here the available production of the time t is

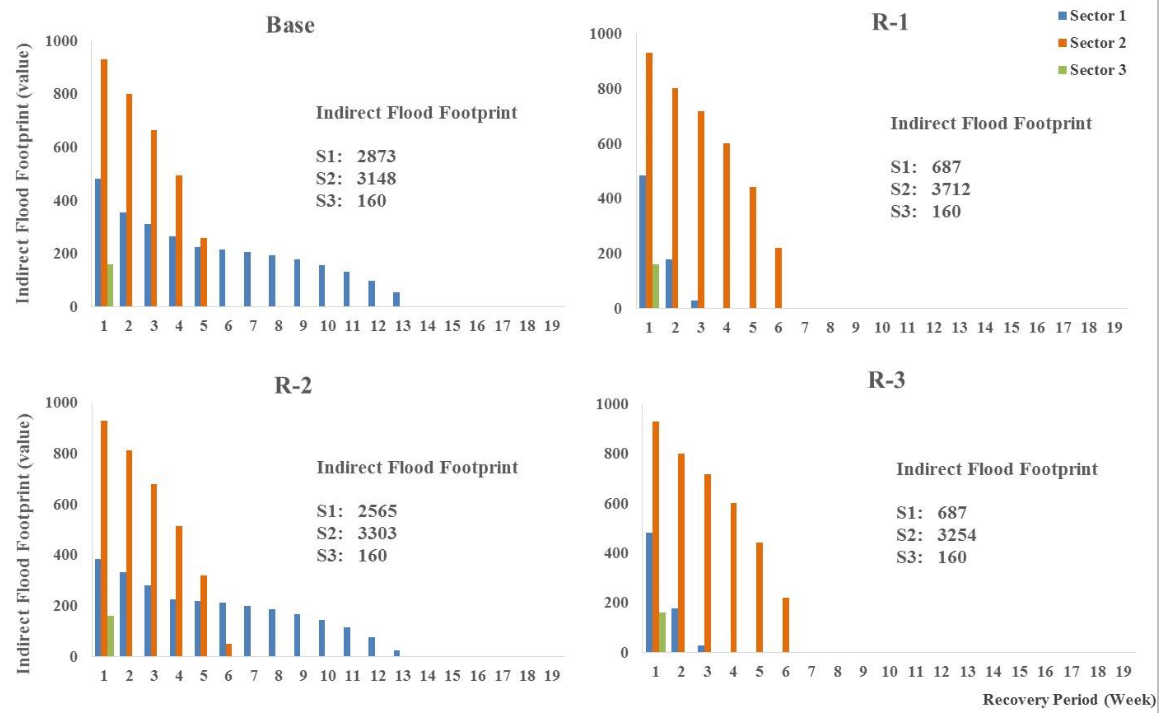
$$\begin{cases} {x_{S1}}^{t} = x_{lab\_S1}^{1}, \\ {x_{S2}}^{t} = x_{cap\_S2}^{1} \\ {x_{S3}}^{t} = \min(x_{cap\_S3}^{t}, x_{lab\_S3}^{t}) \end{cases} \quad (4.36).$$

Table 4.6. Results of critical constraint factor scenarios.

Scenario	Critical Constraint Factor	Recovery Period	Indirect Flood footprint	Total Flood Footprint
Base	3 sectors are constrained by both labour and capital	14 Weeks	6182	10532
R-1	S1 is labour[1]	7 Weeks	4559	8909
R-2	S1 is capital	14 Weeks	6027	10377
R-3	S1 is labour and S2 is capital	7 Weeks	4559	8909

1. If there is no other notifications, the sector is constrained by both labour and capital factor.

Scenarios R-1 and R-3, Scenario Base and R-2 have similar indirect flood footprint trends according to the estimation (Figure 4.4). Scenarios R-1 and R-3 only need 7 Weeks to recovery, while Base and R-2 take almost twice as much time to return to pre-disaster economic levels. Meanwhile, R-1 and R-3 resulted in 4559 indirect flood footprints, which is only 75% of that in Base and R-2. In spite of both labour and capital influencing the production capacity of the industry, there is no evidence to show that labour and capital have an immediate relationship through this research. These two variables have their own recovery paths and affect the outcomes in different ways; labour is an exogenous input while capital is an endogenous factor. Distinguishing the critical constraint factors that affect the available production or production capacity of sectors is the basic requirement for the economic consequence estimation and analysis of disasters.



Scenario Base shows the original recovery scheme that all the 3 sectors are constrained by both of labour and capital; the critical constraint factor of S1 in Scenario R-1 is labour and in Scenario R-2 is capital. Scenario R-3 shows that the critical constraint factor of Sctor 1 is labour and of S2 is capital.

Notes: the horizontal axis shows the recovery period and the whole recovery process starts from the first week (the number of the horizontal axis is 1) after the disaster.

Figure 4.4. Indirect flood footprint of three sectors under the four types of critical constraint factor scenarios.

4.3.5. Sensitivity to Import and Basic Demand

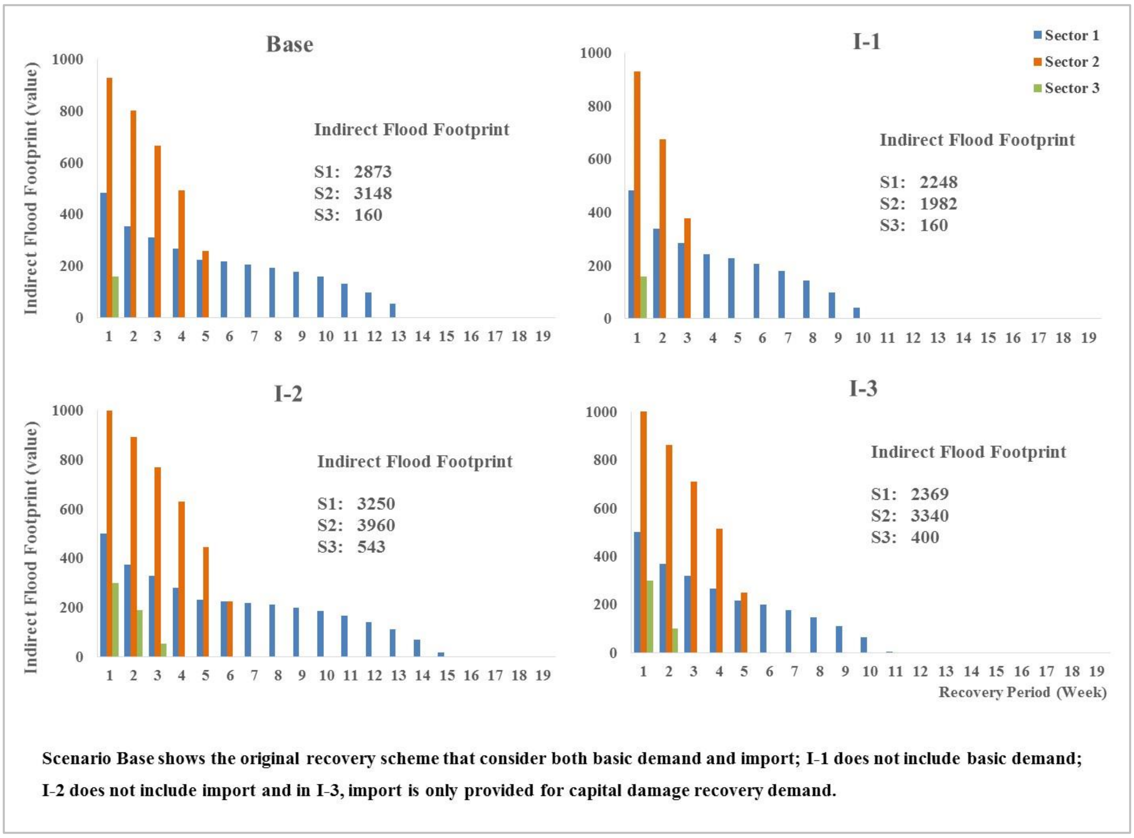
Basic demand and imports at each step decide the percentage of production that is allocated to industrial capital rebuild demands. Basic demand can be different in each stage for one disaster, which will result in a different recovery time and indirect flood footprint. Scenario

Base and I-1 illustrate how the basic demand affects the recovery process (Table 4.7). It is clear that without a basic demand in each step, the local economic system only takes 11 weeks to rebuild (Scenario I-1), and the recovery period and indirect economic loss of S1 and S2 become shorter and less. There is no change for S3 because the recovery speed of S3 is only 1 week. In general, more production used to support basic demands, less goods allocated to capital recovery demands, the longer the time required for total recovery.

Table 4.7. Results of import and basic demand scenarios.

Scenario	Recovery Path	Recovery Period	Indirect Flood footprint	Total Flood Footprint
Base	Both of basic demand and imports are considered	14 Weeks	6182	10532
I-1	Without basic demand	11 Weeks	4391	8741
I-2	Without import	16 Weeks	7753	12103
I-3	Imports only for capital reconstruction	12 Weeks	6108	10458

Import is a vital supply source for the recovery of an economic system; which part of the process introduces imports has become a question. In some reality cases, the local economic system will never return to pre-disaster level without imports due to low productivity of the local industries. However, in out hypothetical numerical example, the production of the local economic system can also be satisfied without import. Three import scenarios are compared here: imports in the Base Scenario exist during the whole process; Scenario I-2 do not consider import but rely only on own production; in Scenarios I-3, imports are only used for industrial capital damage recovery, so that once the capital productivity of the sector returns to pre-disaster level, import will end. As demonstrated in Table 4.7, without import scenario (I-2) has the longest recovery period and the largest flood footprint. If imports are only allocated to capital reconstruction/recovery demand (I-3), the economic system and each sector will need a shorter time to recover and result in a lower indirect flood footprint (Figure 4.5), because the reconstruction improves the production capacity. The independence of the economic system determines how import affects total recovery. The higher the independence from external production before the disaster, the lower the possibility for economic system recovery without import; conversely, the higher the amount of imports, the less time required for post-disaster recovery.



Notes: the horizontal axis shows the recovery period and the whole recovery process starts from the first week (the number of the horizontal axis is 1) after the disaster.

Figure 4.5. Indirect flood footprint of three sectors under the four scenarios.

4.4. Discussion

Different assumptions regarding variations in the Flood Footprint Model result in different recovery processes of the local economic system. Some of the required parameters in the Flood Footprint Model are not easily accessed; the model outcomes are extremely sensitive to these factors, and sensitivity analyses should be conducted for better disaster assessment. As shown in Section 4.3, two types of sensitivity analysis to the model outputs based on the hypothetical numerical example (Table 4.1) are taken into consideration in this research. The first type is sensitivity to model related parameters, including alternative labour and capital restoration, imports and basic demand. Degraded labour productivity in the aftermath can be calculated through real data, but the recovery curve of labour productivity used in the model must be selected carefully. Regardless of whether recovery curves are linear or nonlinear, the uncertainty of labour restoration should be considered during the modelling process. For the capital recovery, according to some real post-disaster recovery plans, most of the investment in the first stage is allocated to priority industries, leading to the damaged sectors not recovering simultaneously during the recovery process. In addition to the demand of household capital loss added in the final demand aftermath, household adaptive consumption behaviour also leads to changes in the final demand. Consumption behaviour of households is affected by many parameters, such as import capacity, local culture and basic consumption capacity. Some products and services are necessary for human life, and how to reorganize them in a recovering economic system is also an urgent problem that needs to be addressed (Steenge and Bočkarjova, 2007). The second type is sensitivity to quality of post-disaster governance. Here I only focus on various delayed recovery conditions, which are caused by incomplete governance. Regardless of whether the delay factor is labour or capital, during the delay period, all the affected sectors remaining damaged and suffering the accumulated indirect flood footprint. Such an accumulated effect can increase the flood footprint and extend the recovery period of the whole economic system.

The rationing scheme seeks to reflect the decision of how to prepare for the disaster recovery stage from the perspectives of various economic agents, including government agencies or households. It is hard to say which rationing scheme is preferred, but by comparing the different options for resource allocation, people can select an optimal way to reconstruct the linkages of each industry and recover the pre-disaster economic balance. Several economic situations in the affected region should be considered in this part, such as sector substitutability. If the substitutability of some local sectors is strong, then the substitution will reduce the impact on the affected production and sectors in the recovery process (Hallegatte, 2008).

Despite several assumptions being made in the Flood Footprint Model, the approach used in this paper is currently the most appropriate way to incorporate productivity with capital and labour constraints and adaptive household consumption behaviour. It is suitable only for one sudden-onset flood in a single region. However, it will be continually improved and applied to single disasters in multiple regions.

4.5. Summary

This chapter is the first illustration of the Flood Footprint Model in the case of a single flood disaster. A hypothetical example (with the 3×3 IO Table 4.1) was used to verify the mathematical equations of the model. Thus, the model improved by this research can illustrate how the linkages among sectors are rebuilt by considering the factors that influence the local economy after a disaster shock. This model provides a temporal evaluation of total production in each period. According to the scales of flood disasters and the final aims of the research, the flood footprints of each disaster per week, per month or per year can be estimated. In contrast to other disaster models, this Flood Footprint Model is more externally oriented and better fits reality. It not only considers the degraded capital or labour production in each time period but also contains the basic human needs (basic demand) and imports over the entire process.

For investment in flood risk management options, it is critical to identify the 'blind spots' in critical infrastructure and vulnerable sectors in the economic supply chains and social networks. This approach allows for sufficient adaptation to the immediate and long-term damage due to a flood event. Adaption to flood risk is not limited to the area that suffers the direct damage. It also extends to the entire socioeconomic networks, and this factor must be considered to minimize the magnitude and probability of cascading damage to regions not directly affected by the flood.

At the level of flood risk mitigation responsibility, a flood footprint accounting framework would provide an alternative way to allocate financial responsibility for flood risk mitigation interventions by incorporating the value of all stakeholders' economic capacities in the local/regional/national supply chains. This approach could potentially reduce the financial burden of the government for flood risk management and spread the cost among major stakeholders in the supply chain, based on the 'who benefits, who pays' principle. In other words, if it turns out through a proper flood footprint assessment that organization(s) x or y benefit in a large way from flood defences, then alternative flood management payment schemes could be considered. At a communication level, the flood footprint could be an excellent concept to enhance business and public awareness of the possible damage they may suffer and of the total damage a flood can cause.

Chapter 5 Flood Footprint Model Illustration II: Beijing 721 Urban Flooding Event

This chapter is an account of the first time the Flood Footprint Model has been applied to a real single-flood case. The event of Beijing 721 urban flooding, which occurred in Beijing, China on July 21th, 2012, was selected as the case study in this chapter. Apart from indirect flood footprint estimated through the Flood Footprint Model, this section offers various types of sensitivity analyses to test the feasibility and flexibility of the Flood Footprint Model under different recovery scenarios.

5.1. Introduction

The study area is Beijing, the capital city of People`s Republic of China and a megacity with high global influence from many perspectives, including economical, political and educational. It is located in northern China with a land area of 16801 km^2 and is surrounded by Hebei and Tianjin provinces. This city is the second most populous city proper in the world, with a population of 21.7 million in 2017; it is also the second most populous capital city and contributes 2.57 trillion CNY (290 billion GBP), about 3.45% of the total GDP in China. On July 21th, 2012, Beijing suffered the heaviest rainfall in the last 60 years, triggering severe urban flooding. During the 16 hours of rain, the average precipitation was recorded as 170 mm, and the worst affected area in Beijing--Fangshan District received 460mm of rain. This disaster severely affected people and capital in the Beijing area: 79 people died and 1.9 million people were affected, either injured or evacuated; over 10 thousand houses were destroyed and more than 500 flights were cancelled or delayed. The total economic loss of the Beijing 721 urban flooding reached 11.64 billion Chinese Yuan.

5.2. Data Sources

This case draws mainly on three kinds of data sources. The first one is the official data source: the input-output table of Beijing in the year of 2010 from Beijing government was used as basic data in my model; technical coefficient (A), industrial outputs and final consumption of 42 sectors before disaster have been taken from this table. The code and name of these 42 sectors are shown in Table A1 in the Appendix. Data on industrial and household capital stock, employment and GDP of Beijing in 2011 have been obtained from Beijing's Statistical Yearbooks. The second data source is news. Data regarding the affected population and the recovery time of transportation (including flights, railways and highways) due to this flooding have been taken from the related news items. The last source is constructed from my own assumptions, as this kind of data is not available, such as labour productivity recovery path and household consumption behaviour adaptation (basic demand). All the input data and results are on a weekly basis and the monetary unit is the Chinese Yuan (1 million Yuan =0.11million British Pound), the basic unit of currency of in the People`s Republic of China. CNY is the currency sign used to refer to the Chinese Yuan.

5.2.1. Capital

In any real case, information concerning destroyed industrial capital can be obtained from insurers or government statistics. According to statistics held by the Beijing government, the total economic loss was estimated at 11.64 billion CNY, and is considered the total capital loss of the Beijing area. Of the 42 sectors, actual damage data is only available for the agricultural sector (S1) and cultural sector (S41); estimated capital loss for water conservation (S37), energy supply (S25, S26 and S27), construction (S28) and medical (S40) sectors are based on related news, with the remaining capital loss equally divided between the other sectors. Details of industrial capital loss is included in Table A2 in the Appendix. Household capital damage information is difficult to obtain because of privacy protection, even though insurers hold this information. Here, the damaged household capital is assumed as 0.05% of total household capital stock, since the damage to houses was concentrated in Beijing's rural areas. Household capital is typically within the sectors of electronics and manufactured products (S19, S20 and S25), transportation equipment (S18), construction (S28) and maintenance services (S24). Thus, 50% of the damaged household capital is attributed to S28, and 10% is allocated to the other five sectors, respectively.

5.2.2. Labour

The labour production capacity recovery is set exogenously. Reduced labour productivity is not accessible in many practical cases. Here, an approach is offered to estimate the changes in labour productivity. Variation in labour time is used as an indicator to measure the variation of labour productivity, which can be calculated through morbidity counts and transport delay times. Figure 5.1 demonstrates the process of measuring labour constraints in terms of labour time loss induced by a flooding event. When considering morbidity due to different reasons, more attention is paid to delay induced by injury, evacuation and transport disruptions, among which I further consider delays due to flight, railway and highway disruption. With each element's share of impact in the total morbidity, the effect of injury, evacuation, flight delay, railway delay and highway delay on industry can be calculated. Next, the total labour time loss in each case can be estimated by multiplying the average time lost for each person affected and added up to obtain the total industrial labour time lost due to the disaster. Finally, through comparison of the total industrial labour time loss and original industrial labour time, the percentage reduction in industrial labour production capacity can be obtained. This study assumes that all the sectors have the same labour constraints and the same recovery path. The labour productivity for each sector decreased by 4% after this urban flooding through my calculation. Then it recovered to 98% and 99.5% in the second and third week, respectively, and completely recovered in the fourth week according to my assumptions.

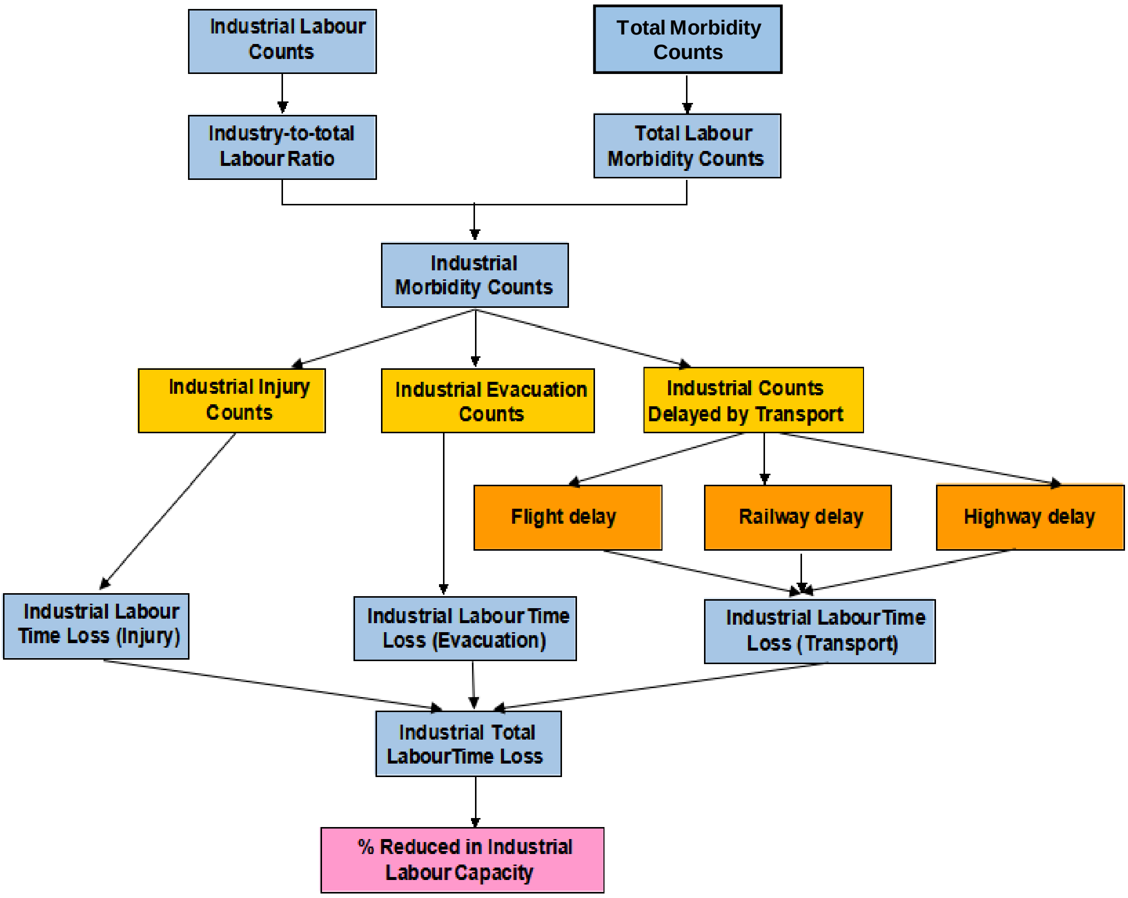


Figure 5.1. Labour constraint estimation.

5.2.3. Basic Demand

We often assume that life necessities, also called the basic demand, in the disaster aftermath tend to gain greater significance. This concerns the final demand in the Flood Footprint Model and is equal to the minimum amount of food, clothing, energy and medical services. Because of lack of data in this area, the basic demands for food (S1 and S6), clothing (S7 and S8), energy (S25, S26 and S27) and medical services (S40) are assumed to be half the pre-disaster level, while consumption of other products is zero in this case. The basic demand can be different in each stage, but for this study, it is assumed as a fixed amount in each week.

5.3. Results

5.3.1. Flood Footprint Assessment

In the cases of previous data condition, the total flood footprint of the 'Beijing 721 urban flooding event' is estimated at 21.19 billion CNY. The direct flood footprint of 11.64 billion CNY, obtained from official documents, represents 55% of the total flood footprint; the other 45% of the flood footprint is indirect part, and estimated as 9.55 billion CNY. The duration of this urban rainfall was only 16 hours. Yet, the total economic loss resulting from this event equals almost 1.18% of the total GDP in the Beijing area in the year 2012. Meanwhile, it took 42 weeks for complete industrial recovery back to pre-disaster levels when imports are taken into account during the whole recovery period. As shown in Figure 5.2a, most of the recovery process is concentrated in the first ten weeks. Compared with capital constraints, labour has more influence on the total production capacity, particularly in the first five weeks. The recovery of industrial damaged capital is rapid in the beginning and then slows down (Figure 5.2b). Within 42 sectors, capital recovery in S27 (water production and supply) takes the longest, at 42 weeks, followed by S26 (gas production and supply) at 13 weeks. Reconstruction in the other sectors is completed within the first five weeks. This scenario is an ideal situation and does not consider other effects like the quality of governance.

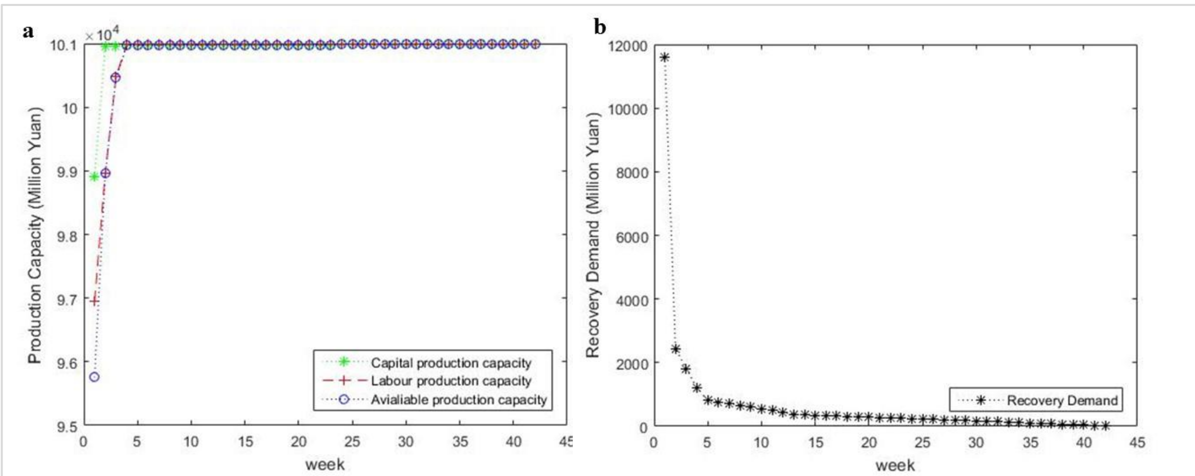


Figure 5.2. Recovering process of the case study.

5.3.2. Industrial Flood Footprint

Three-sector theory (Fisher, 1939, Clark, 1967) divides an economic system into three parts: primary industries (as the industry of extraction and collection of natural sources), secondary industries (manufacturing industries) and the tertiary/services industries (industries that provide goods and services to customers). In this case, the only primary industry is the agriculture sector (S1), secondary industries comprise S2-S28, while S29-S42 belong to the tertiary industry. According to my estimation, the tertiary industry contributes the largest part, nearly 52% (11096 million CNY) of the total flood footprint caused by 'Beijing 721 urban flooding event', followed by the secondary industry at 40% (8438 million CNY) and the primary industry at 8% (1665million CNY). The indirect economic loss is therefore 8%, 65% and 35% of the total flood footprint for the primary, secondary and tertiary industries, respectively. Among the secondary industries, half of its flood footprint is in construction (S28), electricity production and supply (S25), and gas production and supply sectors. Among the tertiary industries, the sectors of water conservation (S37), transportation (S30) and finance (S33) share half of flood footprint.

From an individual sector perspective (Table A2 in Appendix), the flood footprints of seven sectors are greater than 2000 million CNY. As seen in Figure 5.3, regarding the first ten sectors with high flood footprint, seven sectors come from the tertiary industry, two from the secondary industries and one from the primary industries. In particular, the construction sector (S28) has the largest flood footprint with 2590 million CNY, accounting for over 12% of total flood footprint, followed by water conservation (S37) and transportation (S30), sharing nearly 10% (2063 million CNY) and 9% (1962 million CNY), respectively. Meanwhile, ten sectors from the secondary industries with the lowest flood footprint are less than 100 million CNY, and include the sectors of scrap and waste (S23, 23 million CNY), general technical services (S24, 36 million CNY) and textiles (S7, 39 million CNY).

5.3.3. Direct and Indirect Flood Footprint

In terms of the relationship between industrial direct and indirect flood footprint, it is clear that the indirect flood footprint is not determined immediately by the direct impact. Taking the first ten sectors with high flood footprints as examples (Figure 5.3), in these ten sectors, only two sectors contain larger indirect flood footprints than the direct footprints. The indirect flood footprint in S29 is 29 times higher than its direct footprint, and the ratio in S28 is 1.6. At the same time, the indirect impact is just 3% of its direct flood footprint in S37. The same direct flood footprints do not necessarily result in the same indirect flood footprint, such as sectors S28 and S41. Although both direct economic impacts are 1000 million CNY, the gap with their indirect flood footprints is 1400 million CNY. In other words, a high direct flood footprint does not mean high indirect impact, such as S27 and S29. The direct impact of S27 is 500 million CNY while the indirect impact is only 59 million CNY; while in S29 the direct footprint is 20 million CNY, its indirect impact is 580 million CNY. Therefore, the indirect flood footprint of each sector is not only influenced directly by the capital damage of other sectors, but primarily depends on the internal linkages between these sectors.

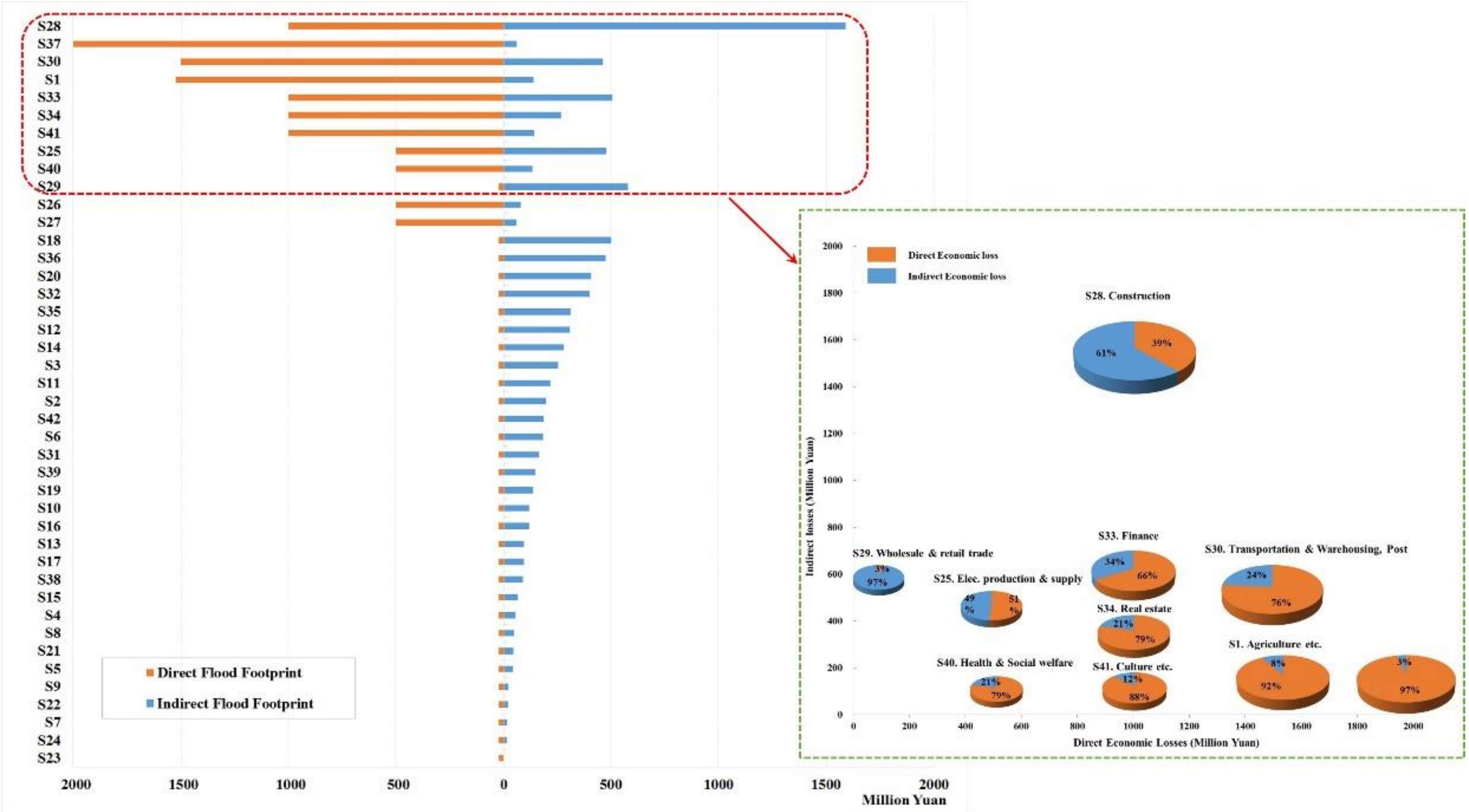


Figure 5.3. *Flood footprints of 42 sectors in Beijing and the ratios for direct and indirect flood footprint of the first 10 high flood footprint sectors.*

5.4. Sensitivity Analysis

The flood footprint of a single disaster event depends to a large extent on the final aim of the study and the variation of parameters in the Flood Footprint Model. As a mathematical model, there are many uncertainties regarding the input and output in my Flood Footprint Model. However, it still lacks actual data to validate the results due to the complexity of economies. Sensitivity analysis of the model's variables is therefore an essential and effective way for improving the accuracy of the model's results. This section offers a series of sensitivity analyses of the alternative parameters of the Flood Footprint Model, including the sensitivity to critical constraint factors, labour and capital productivity recovery paths, import and basic demand, and delay resulting from ineffective governance; and also provides a range of flood footprints of the case 'Beijing 721 urban flooding event' under different conditions. The input data described in Chapter 5.3 is set as the basic data condition of Base Scenario, while the results of Base Scenario are shown in Chapter 5.2.

5.4.1. Labour Productivity Recovery Scenarios

In this study, the influence of labour constraints on an economic system is quantified as the labour impact on industrial productivity. For a particular natural disaster case, by employing the special labour recovery scheme, the tendency of the remaining productivity and indirect flood footprint of each sector will also reflect special characteristics. However, as previously mentioned, the ways in which the industrial labour force of an economy recovers to pre-disaster level after a shock is still unknown. In order to analyse how the labour constraints affect the final results of the case, four scenarios that include four possible labour recovery plans are compared here. It should be mentioned that apart from the labour productivity recovery plans, other input data remain the same in these scenarios. As listed in Table 5.1, the specific data plan is used in the Base Scenario; while recovery paths of labour productivity (LP) in scenarios L-1, L-2 and L-3 are linear, polynomial and logarithmic trends, and the corresponding equations are $LP=0.01t+0.96$, $LP=0.005t^2+0.96$ and $LP=0.03\ln(t)+0.96$ (where t is the time period and the unit is week, here $t \geq 1$), respectively. According to these LP trends, the labour recovery period for Scenario L-1 is four weeks, and for the other three is 3 weeks.

Table 5.1. Results of labour productivity recovery scenarios.

Scenario	Labour Recovery Path		Recovery Period (week)	Indirect Flood footprint (million CNY)	Total Flood Footprint (million CNY)	Percentage of Indirect flood footprint
	Equation	Recovery Period (week)				
Base	Specific data	3	42	9555	21195	45%
L-1	LP=0.01t+0.96	4	42	13056	24696	53%
L-2	LP=0.005t^2+0.96	3	43	12560	24200	52%
L-3	LP=0.03ln(t)+0.96	3	42	9679	21319	45%

1. t is the time period and the unit is week, here t ≥1.

The flood footprints and recovery periods of these four labour productivity recovery scenarios are also shown in Table 5.1, Figure 5.4, which describes how the labour recovery scheme affects the available productivity. It is obvious that the labour recovery scheme has a significant influence on the recovery process and the final flood footprint of the case. The available productivity shows different trends in each scenario and corresponds closely with the labour productivity trends. Meanwhile, in all the scenarios, the first five weeks explain the majority of their indirect flood footprints. Despite the direct flood footprint of these scenarios being the same (11640 million CNY), the Base Scenario has the smallest flood footprint with 21195 million CNY, while Scenario L-1 has the largest one, nearly 24696 million CNY, and the indirect flood footprint of the latter (13056 million CNY) is 1.37 times of the former (9555 million CNY). The same labour recovery period can result in various flood footprint results, such as Scenario Base, L-2 and L-3. Scenario L-2 requires longer (43 weeks) to recover with a flood footprint of 24200 million CNY, and others are estimated as 42 weeks. In the case of the Beijing 721 urban flooding, the L-1 and L-2 scenarios are supposed to raise higher flood footprints than the Scenario Base and L-3. But this does not mean that the linear and polynomial recovery trends of labour have a more significant influence for other cases; rather, such results mainly depend on the features of the cases. Figure 5.5 shows the characteristics of the first ten sectors with the highest flood footprint in each scenario. According to the estimation, the entire flood footprint level of Scenario L-1 and L-2 is 700-2900 million CNY,

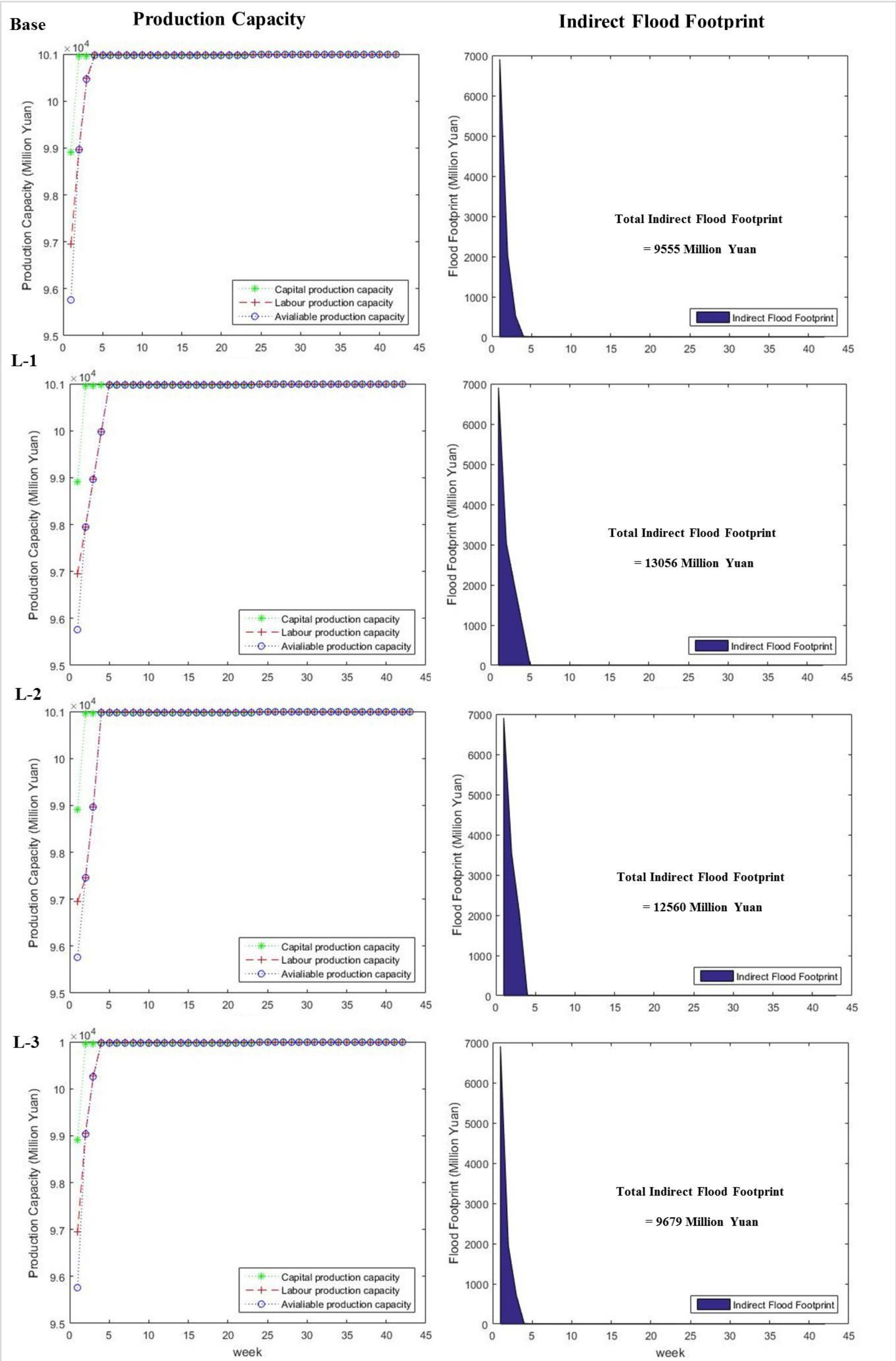


Figure 5.4. Recovering processes of the four labour recovery scenarios.

much higher than the flood footprint range of the other two scenarios, 600-2600 million CNY. There is no significant difference in the constitutions of these ten sectors in the four scenarios, regardless of the type of labour recovery path. S28 is still in the first place with a flood footprint larger than 2500 million CNY, but in the tenth sector, the scientific research sector (S36) and the transport equipment sector (S18) are ranked as the tenth sector in Scenarios L-1 and L-2, respectively, while both the Base Scenario and L-3 are still the sectors of wholesale (S29).

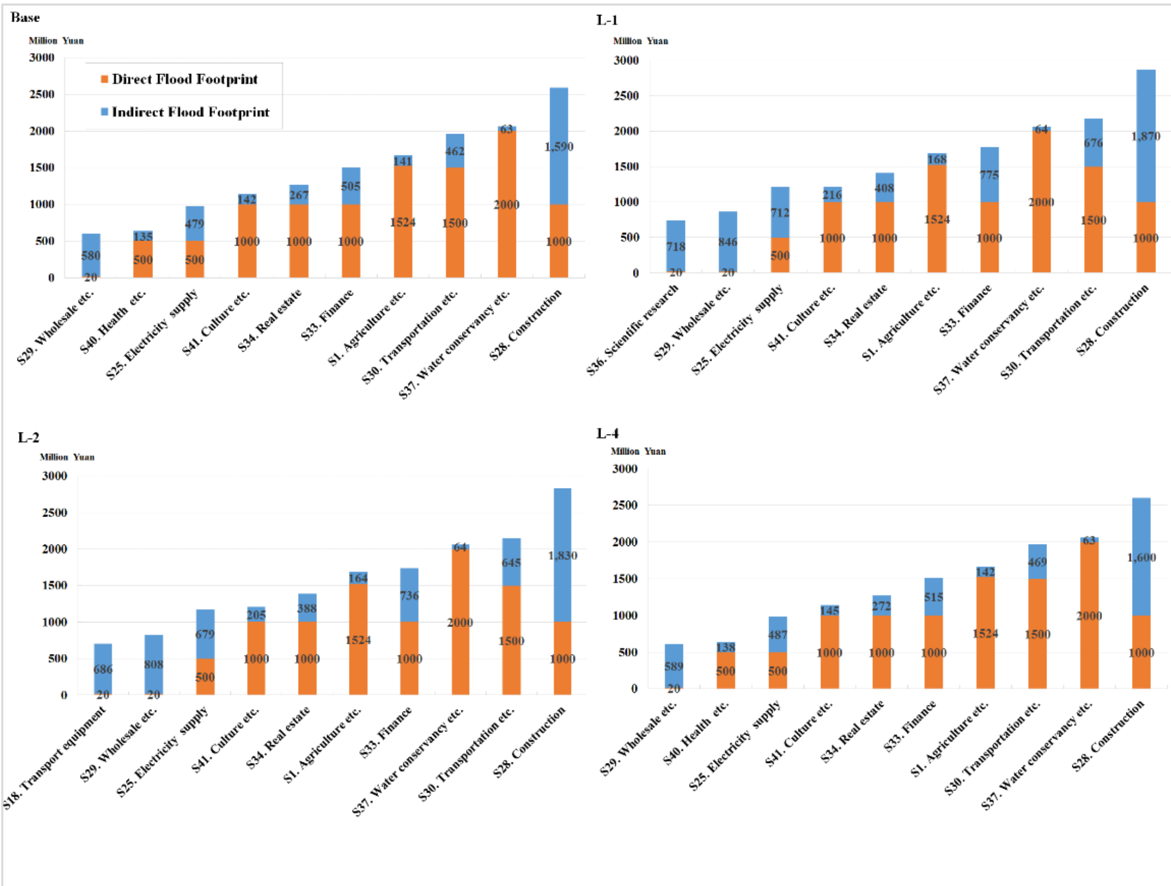


Figure 5.5. The first 10 sectors with the highest flood footprint of the four labour recovery scenarios.

5.4.2. Capital Productivity Recovery Scenarios

In accordance with regulation 5.3.2 of the ‘Emergency Plan for Flood Control in Beijing (2012)’ that was designed and issued by the Beijing government, the functions of sectors related to water conservation (S37), transportation (S30), information transmission (S32) and energy support that includes electricity (S25), water (S27), gas and oil (S26), need to be restored as a priority (Beijing Government, 2014). Hence, these sectors are assumed to be the key sectors of the regional economy for the case Beijing 721 urban flooding event. Four types of alternative recovery plans of these industrial capitals are employed for analyzing the influences on capital recovery, while other input parameters remain unchanged from the data condition of the Base Scenario (Table 5.2). The detailed industrial capital recovery plans for the four scenarios are: 1) all sectors are recovered from the first week in Base Scenario; 2) key sectors are supposed to recover from Week 1, while others, from the fourth and eighth week in Scenarios C-1 and C-2, respectively; 3) Scenario C-3 assumes that the reconstruction of key sectors is from Week 9 and others from Week 1. Table 5.2 provides the model results of each scenario and it is clear that various capital recovery plans lead to different flood footprints for a specific case. The average recovery period of these scenarios is 42 weeks, Scenario C-3 has the largest flood footprint (32532 million CNY), almost 1.5 times of the smallest, that of the Base Scenario; the indirect flood footprint of the former is nearly 2.2 times of the latter. Both indirect and total flood footprints are higher in the other two scenarios C-1 and C-2 and are also higher than those of the Base Scenario. There is no direct evidence to show the relationship between the numbers of affected sectors with longer waiting recovery times and the indirect flood footprint. However, from a mathematical perspective, the longer the waiting time for the reconstruction of the damaged industrial capital is, the larger the indirect flood footprint of the economy. For example, in the Base Scenarios C-1 and C-2, when the recovery of other sectors is longer, from the first week to the eighth week, the indirect flood footprint also increases from 9555 million CNY in the Base Scenario to 19733 million CNY in Scenario C-2.

Table 5.2. Results of capital productivity recovery scenarios.

Scenario	Recovery Path	Recovery Period (week)	Indirect Flood footprint (million CNY)	Total Flood Footprint (million CNY)	Percentage of Indirect flood footprint
Base	All sectors from Week 1	42	9555	21195	45%
C-1	Key sectors from Week 1, others from Week 4	42	12503	24143	52%

C-2	Key sectors from Week 1, others from Week 8	42	19733	31373	63%
C-3	Key sectors from Week 8, others from Week 1	43	20892	32532	64%

Figure 5.6 presents the recovery processes for the total available production capacity and indirect flood footprints under the four scenarios with different kinds of industrial capital recovery paths. The available industrial productivity at each stage is a result of the comprehensive effect of labour and capital constraints. That is why the blue line (available production capacity) in each scenario does not simply coincide with the green (capital production capacity) or the red line (labour production capacity). The distance between the blue line and other lines demonstrates the primary influencing factors on the available capacity. For example, for C-2, the distance between the blue line and the red line is shorter than that between the blue and green lines in the first three weeks. This means that during this period, labour has more influence on total capacity; after the third week, the blue line approaches and meets the green line, indicating the larger impact of capital constraints on total capacity. Regarding the indirect flood footprint, even though the economic system has recovered within 42 weeks, more than 90% of the indirect flood footprint occurs in the first five weeks in the Base and C-1 scenarios; in the other two scenarios, the largest indirect flood footprint comes in the eighth week. When considering specific industries, we can see that the capital recovery plans make a significant difference to some sector`s flood footprint, such as the construction sector (S28) in this case study.

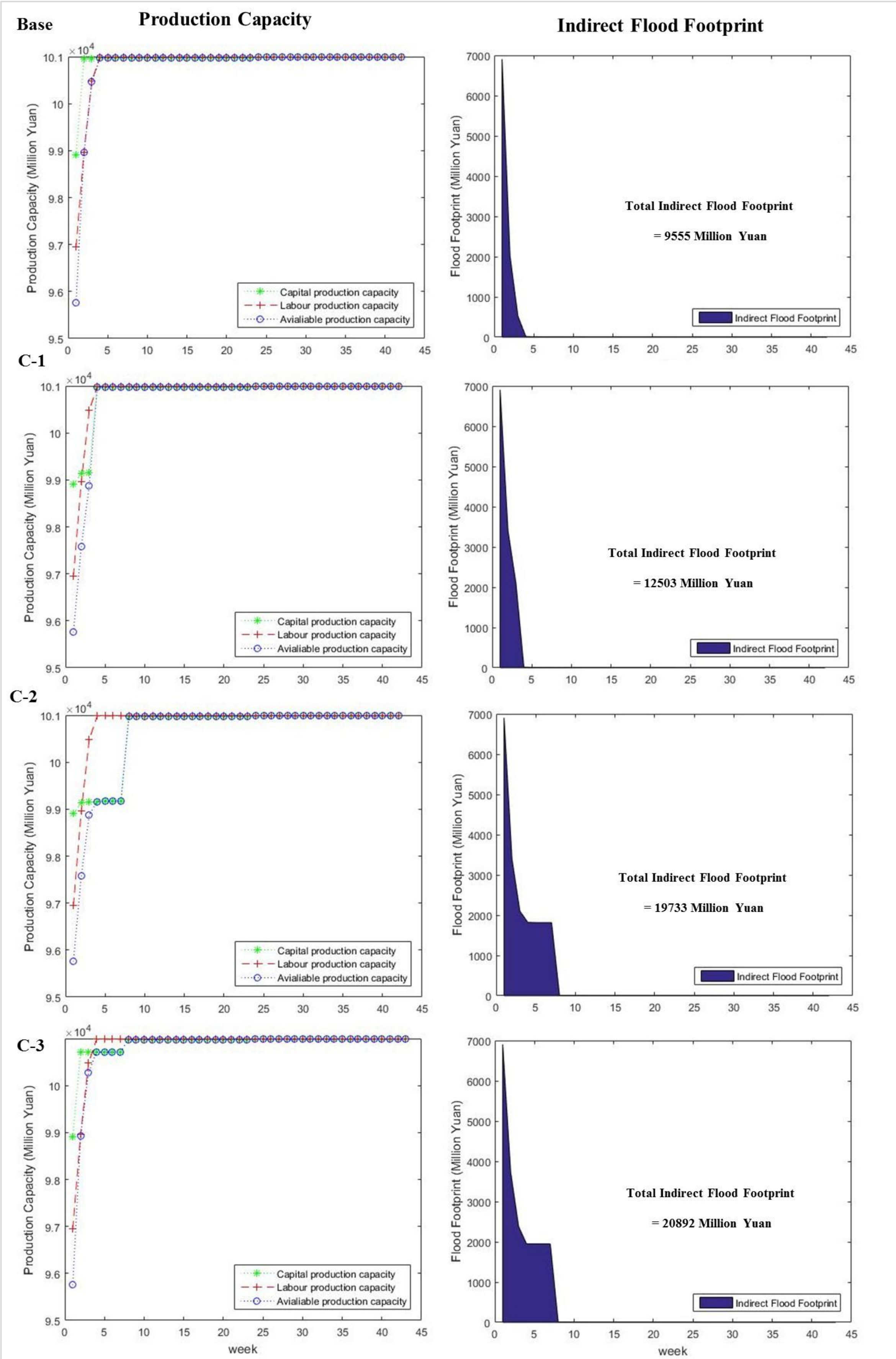


Figure 5.6. *Recovering processes of the four capital recovery scenarios.*

As shown in Figure 5.7, it is evident that the flood footprint of S28 is entirely different depending on capital recovery conditions. If S28's recovery begins in the first week, as it does in the Base Scenario and C-3, the indirect flood footprint only accounts for 61% (1590 million CNY) of its total flood footprint. However, when the recovery time is delayed to the fourth week, as it is in Scenario C-1 and to the eighth week in Scenario C-2, such ratios are respectively increased to 85% and 91%, as 5558 and 9726 million CNY. By contrast, the recovery plan for capital recovery has less impact on key sectors S25 and S37 because there is little difference in the indirect flood footprints for S25 or S37 among these scenarios. Consequently, economic impact of a sector has no relevance to the 'key sectors', but rather, depends upon its original production capacity and the coefficient that connected it with other sectors.

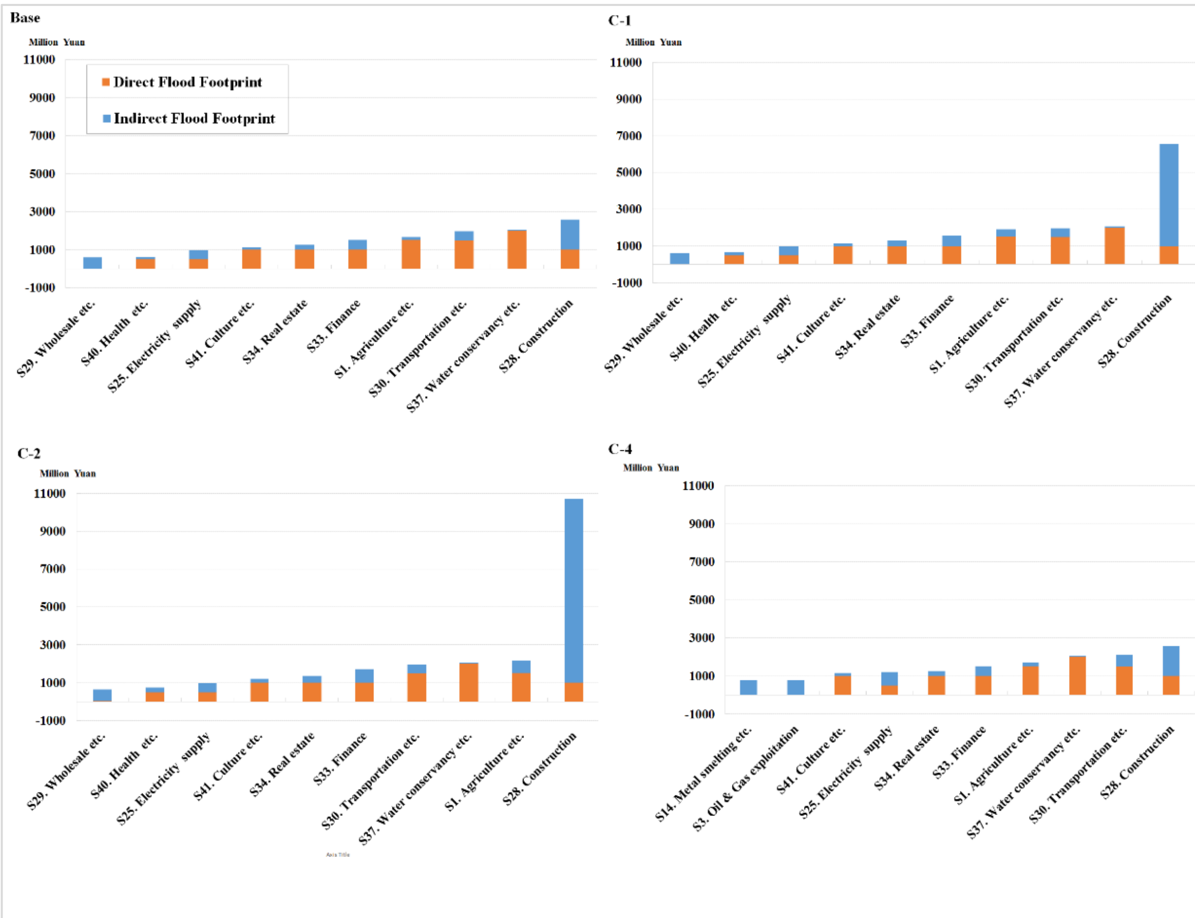


Figure 5.7. The first 10 sectors with the highest flood footprints of the four capital recovery scenarios.

5.4.3. Delayed Recovery Scenarios

Delayed recovery for an economy after a natural hazard event is a universal phenomenon and generally is the result of two factors. First is the political factor, for example, a lack of external assistance, particularly financial assistance, due to bad or inefficient governance; the other is physical causes, for example, imports and rebuilding may be affected by damaged physical infrastructures such as blocked roads. Delay of recovery can occur either in labour or capital, or both in real cases. For the instance, in the case of the Beijing 721 urban flooding event, the primary mission for the transportation system sector after the disaster was to carry out urgent repairs and keep the main roads open for its operations. Reconstruction of the 1012 damaged roads only began 40 days later, with the aim of complete recovery within 2 years (CNS, 2012, AUGUST 21). Thus, the exact timing for recovery of the roads was over one month after the flood. Regarding the whole recovery plan, rebuild and reconstruction are generally followed by post-disaster rescue and relief work, which always leads to delay in the recovery of both the affected labour force and the damaged capital. In order to provide a comprehensive picture of flood footprints caused by delayed recovery, I created six scenarios that respectively focus on four-week and eight-week delayed recovery of labour (Scenario DL-1 and DL-2), capital (Scenario DC-1 and DC-2) and both (Scenario D-1 and D-2) on the basis of the Base Scenario.

Table 5.3. Results of delayed recovery scenarios.

Scenario	Delay factor	Delay period (week)	Recovery Period (week)	Indirect Flood footprint (million CNY)	Total Flood Footprint (million CNY)	Percentage of Indirect flood footprint
Base	None	No delay	42	9555	21195	45%
DL-1	Labour	4	43	21625	33265	65%
DL-2	Labour	8	44	37756	49396	76%
DC-1	Capital	4	45	19887	31527	63%
DC-2	Capital	8	49	34920	46560	75%
D-1	Both	4	45	30269	41909	72%

D-2	Both	8	49	57887	69527	83%

Flood footprints and the recovery process of each scenario are shown in Table 5.3 and Figure 5.8. Compared with the Base Scenario, all the delayed recovery conditions can prolong the recovery period and increase the flood footprint of the regional economy. In turn this increases the percentage of the total flood footprint attributed to indirect impact as the direct flood footprint is fixed. Scenario D-1 and D-2 have the largest flood footprint in the four-week (Scenario DL-1, DC-1 and D-1) and eight-week delay groups (Scenario DL-2, DC-2 and D-2), with a flood footprint of 41909 million CNY and 69527 million CNY, respectively, indicating that the combined impact of labour and capital delayed recovery is much larger than either labour delay or capital delay. For the specific delay factors, such as the Scenario DL-1 and DL-2 that only consider labour recovery delay, indirect flood footprints under the eight-week delay conditions (Scenario DL-2, 37756 million CNY) are larger than that of four-week delay scenarios (Scenario DL-1, 21625 million CNY), mainly as a consequence of the accumulative effect. While awaiting recovery, the industries are still in a damaged condition, producing indirect flood footprints, until the point at which they enter into the recovery and reconstruction period. From this point, the damaged productivity of each sector can be repaired thereby decreasing the indirect flood footprint. Thus, the accumulative indirect flood footprint during the delay of recovery explains the increased part of the total flood footprint and this accumulative effect illustrates why the longer the delay, the larger the flood footprint. In addition, we to the left of Figure 5.8, the lines of available production capacities are closer to labour production capacities in Scenario D-1 and D-2, which demonstrates that labour is the main constraint factor to total indirect flood footprint under these two scenarios.

5.4.4. Sensitivity to Import and Basic Demand

According to the Beijing Input-output table that includes the economic components and production distribution in the Beijing area, the independence of the economy in Beijing city is extremely weak since the normal economic operation of Beijing is heavily reliant on the external production from other regions and countries. As an external source for production, import has a crucial economic influence on Beijing city. As there is a lack of information regarding post-disaster imports and production distribution, I compared different imports in Beijing's economic system recovery period, without import (Scenario I-1), with half imports (Scenario I-2) and 75% imports (Scenario I-3). However, as a consequence, for the 721 Beijing flood, if external assistance was lower than the amount of import capacity in the recovery period, the Beijing economy would not have been able to recover back to pre-disaster levels because there would not have been sufficient goods and services to satisfy completely the demand from inter-industry and other related consumers. The original import capacity then becomes one of the recovery thresholds for Beijing's economic system.

Table 5.4. Results of import and basic demand scenarios.

Scenario	Recovery Path	Recovery Period (week)	Indirect Flood footprint (million CNY)	Total Flood Footprint (million CNY)	Percentage of Indirect flood footprint
Base	Both of basic demand and import are considered	42	9555	21195	45%
I-1	Without import	×	-	-	-
I-2	Half of Imports	×	-	-	-
I-3	75% of Imports	×	-	-	-
H-1	Without the basic demand	21	9492	21132	45%
H-2	Half of the basic demand	28	9513	21153	45%
H-3	Twice of the basic demand	×	-	-	-

Note: '×' means the economic system of Beijing region is not able to recover under such scenarios; '-' stands for no available data.

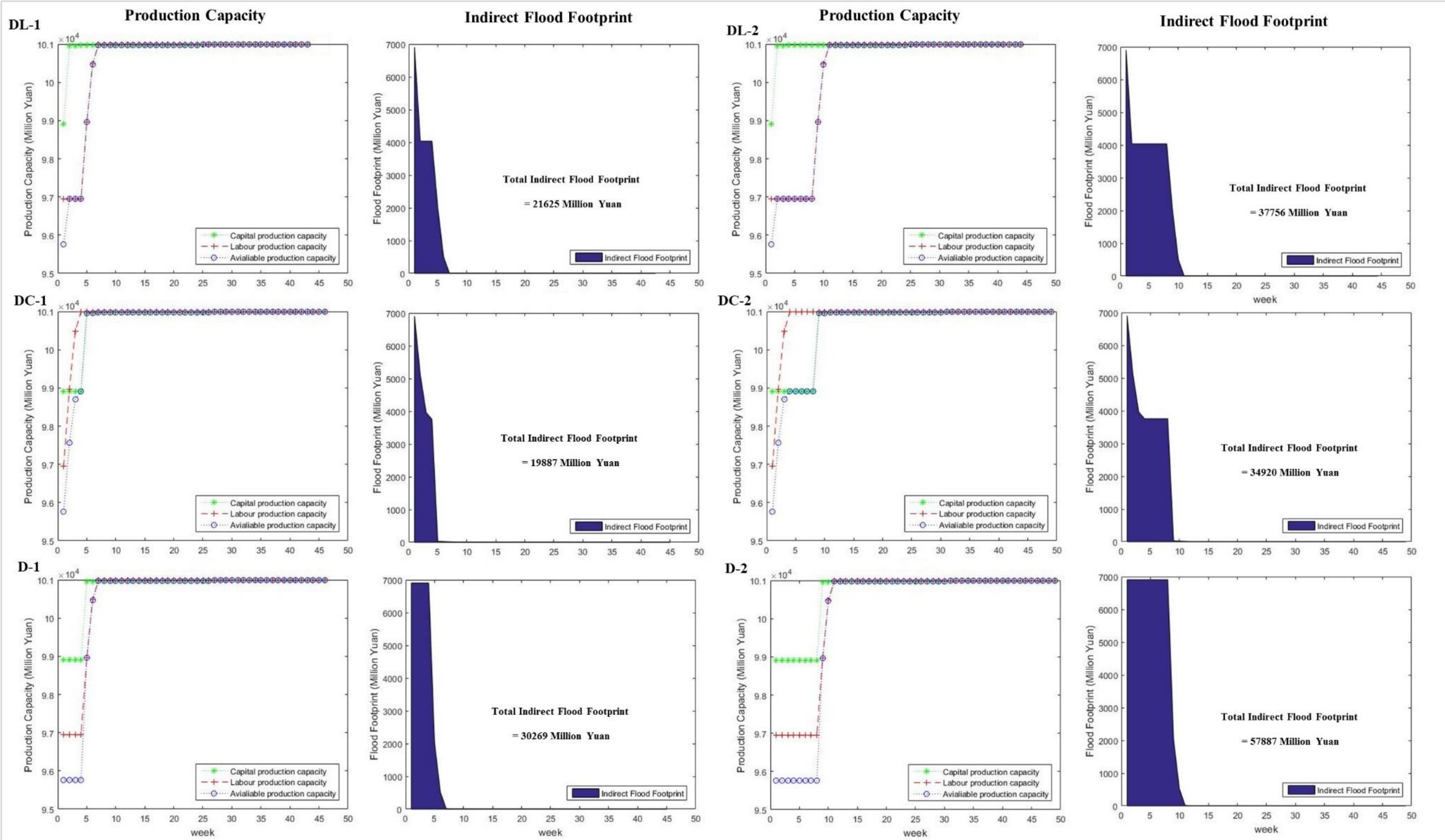


Figure 5.8. *Recovering processes of six delay scenarios.*

The basic demand in this case only refers to eight sectors as mentioned in 3.2.3. The level of basic demand might significantly affect the post-disaster recovery process due to its strong link to the production distribution at all stages. However, there is no available data of the basic demand in the Beijing case, and this thesis only provides three other scenarios to compare the impact of basic demand (Table 5.4). For the Beijing flood case, basic demand does not affect the indirect or total flood footprints, but just has an impact on the recovery period. If basic demand is not considered as a single parameter but is included in the final demand in the recovery period, then the Beijing economy only takes 21 weeks to fully recover (H-1). When the basic demand becomes half of that of the Base Scenario, the recovery period increases to 28 weeks (H-2). However, if basic demand were to double, it would be impossible for Beijing's economy to recover to pre-disaster levels (H-3). Therefore, in conclusion, the less the basic demand at each stage, the shorter time for industrial transaction recovery.

5.4.5. Sensitivity to Critical Factor

In my Flood Footprint Model, the available production that excludes imports at each recovery stage is primarily influenced by two critical factors, labour and capital constraints, and its amount equals to the minimal of the industrial production that was limited by damaged capital and affected labour, as in the Base Scenario. Nevertheless, some practical disaster cases illustrate that industrial recovery is merely constrained by either labour or capital. Here, two hypothetical scenarios are presented to analyse the influence of critical factors (Table 5.5). Scenario K-1 assumes that labour is the only factor that affects all the industrial production capacity, and in K-2, the critical factor is capital.

Table 5.5. Results of critical factor scenarios.

Scenario	Critical Factor	Recovery Period (week)	Indirect Flood footprint (million CNY)	Total Flood Footprint (million CNY)	Percentage of Indirect flood footprint
Base	Both	42	9555	21195	45%
K-1	Only labour	38	8243	19883	41%
K-2	Only capital	42	3910	15550	25%

Note: '×' means the economic system of Beijing region is not able to recover under such scenarios; '-' stands for no available data.

Table 5.5 and Figure 5.9 present the results and recovery process of the two scenarios. The indirect flood footprint of K-1 is 8243 million CNY and accounts for 41% of the total flood footprint (19883 million CNY), and over 95% percent of indirect flood footprint occurs in the first four weeks; K-2's flood footprint is 15550 million CNY with the indirect footprint accounting for only 25% (3910 million CNY), with the majority of K-2 indirect flood footprint generated in the first two weeks. Among the three scenarios, the Base Scenario resulted in the largest economic impact with an indirect flood footprint almost 1.6 times larger than that of K-1 and 2.4 times larger than that of K-2. Compared with a single constraint factor (either labour or capital), the comprehensive effect of both labour and capital has a higher economic impact in the Beijing case. Additionally, there is no evidence to show that a shorter recovery period would result in a smaller indirect flood footprint. Although K-2 induced the smallest flood footprint, it still took the same time (42 weeks) as the Base Scenario to recover. The available production capacity in K-1 completely coincides with labour production capacity in Figure 5.9 due to labour being its critical limiting factor; it also explains the production capacity in K-2.

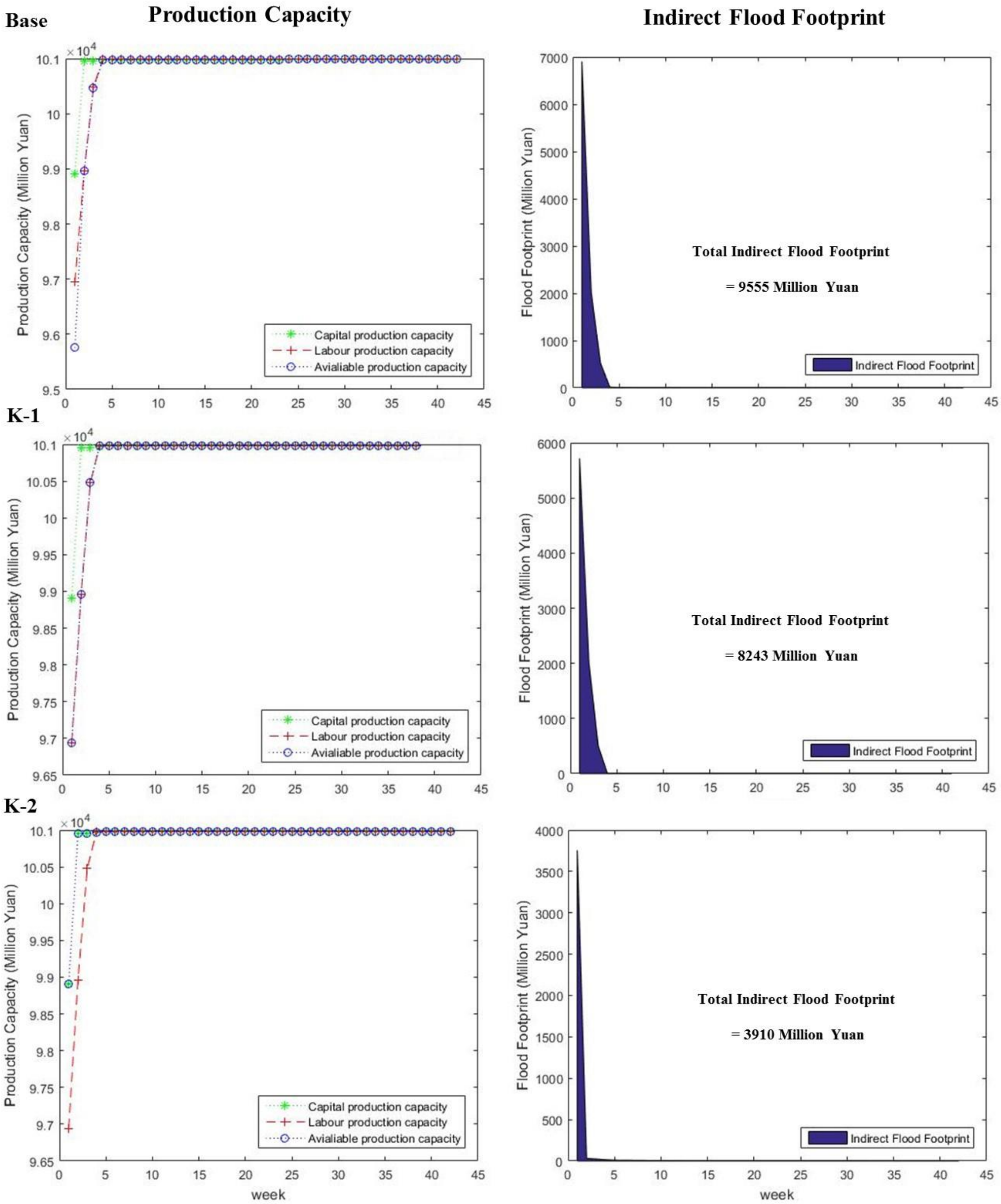


Figure 5.9. Recovering processes of the three critical factor scenarios.

5.5. Discussion

The results show that the tertiary industry accounts for 52% of the total flood footprint of 11096 million CNY; 40% comes from the secondary industry (8438 million CNY) and the other 8% is generated by the primary industry (1665million CNY). The sectors of construction (S28), water conservation (S37) and transportation (S30) account for the largest flood footprint, as much as 2590, 2063 and 1962 million CNY respectively, which represents over 12%, 10% and 9% of the total flood footprint. Such results seem to correspond closely with the industrial output composition of Beijing in 2012. As a post-industrial economy, over 76% of the total outcomes in Beijing city are generated in the tertiary industries, in particular, the Finance sector. About 23% is generated by secondary industries and only 1% comes from primary industries. With regards to the relationship between direct and indirect flood footprint, we can conclude that although direct capital damage influences the indirect economic impact, the recovery process and indirect flood footprint are not determined by the direct economic loss immediately, but depend more on the internal linkages of the sectors. Hence, in a regional economy, a higher industrial direct flood footprint does not mean a higher indirect flood footprint; we can only say that an increase in the capital damage of a specific sector leads to a larger indirect flood footprint.

The flood footprint of 21.19 billion CNY provided here is an underestimate due to lack of actual data for the real case. In order to estimate the sensitivity to alternative parameters, I assumed a series of scenarios that are closer to reality and offer more detailed comparisons and analyses, including alternative labour and capital recovery paths, delayed recovery conditions, different amounts of imports and basic demand, and particular critical factors. No matter what types of sensitivity analyses are undertaken, the results demonstrate that the flood footprint and recovery process of a specific natural disaster can be changed with changes to these parameters in the Flood Footprint Model. The quantity of governance also has a significant impact on post-disaster recovery. Delays caused either by weak governance or damaged physical infrastructure can increase flood footprint due to the accumulated effect. Therefore, sensitivity analysis is an essential part of natural disaster risk analysis and various scenarios should be considered according to the reality data and information.

The study in this chapter still has several limitations. First, various assumptions are made in the modelling process due to some types of data not being available, such as statistical data on labour recovery schemes and basic demand data. Despite the model outcomes being sensitive to these assumptions, the data used in my research is the best from what is available . Second, it is difficult to verify and validate the results from the Flood Footprint Model since there is no statistical data about how sectors and economic systems recover after a natural disaster event. Currently, we can only carry out different types of sensitivity analyses that closely simulate real conditions to reduce the uncertainty of the results. Third, external investment of capital assistance during the recovery period has not been taken into account. Investment is an important part of imports, but due to lack of investment data after the 721 Beijing flood, this study assumed that no other input capital was added after the disaster. Overall, in future research, more detailed information should be collected and more effort should be made to carry out more accurate flood footprint estimations. At this stage, this research is able to assess the flood footprint of a real case, while providing a database and scientific support for single sudden-onset natural disaster risk analysis and management.

5.6. Summary

Beijing 721 urban flooding is the selected case study in this chapter. The total flood footprint of this case is calculated as 21.19 billion CNY, almost 1.18% of the total GDP in the Beijing area in the year 2012. In particular, the direct flood footprint based on the Beijing government statistics was 11.64 billion CNY, accounting for 55% of the total flood footprint; another 9.55 billion CNY is accounted forby indirect flood footprint, using the Flood Footprint Model, amounting to a 45% share of the Beijing flood footprint. It took 42 weeks for the Beijing economy to completely recover to pre-disaster economic level. Wang et al. (2015), adopting the CGE model to estimate the total economic loss of Beijing flooding case, estimated and over 38.64 billion CNY and an indirect loss of more than 27 billion CNY, both figures nearly 17 billion more than those estimated in my research. However, the Input-Output model is a more appropriate measure than the CGE model for assessing economic changes after such a sudden interruption, especially for sudden-onset natural disasters like floods and typhoons due to their variable characteristics. The direct damage by sudden-onset natural hazards occurs in the short term; more exogenous and complex parameters included in the CGE models increase the uncertainty of the outcomes. Different approaches employed in the case lead to a more complete assessment of economic impacts.

Flood footprint is a concept that refers to the direct and indirect economic impacts on the economic system that result from natural disaster events. In this chapter, the Flood Footprint Model was first successfully applied to assessing the indirect flood footprint of a real disaster. As an approach to natural disaster risk analysis, the Flood Footprint Model is able to reveal the comprehensive effects of capital and labour constraints, and display a visible yearly, monthly or weekly recovery process through a mathematical and logical method. Compared with previous studies that focus on a hypothetical numerical example, this study improves the practical application of the Flood Footprint Model in the following ways: firstly through developing a way to quantify the labour constraint, namely converting the percentage of decreased labour productivity to the percentage of reduced labour time. The second improvement is that it integrates the household capital recovery demand into the industrial capital reconstruction demand through distributing the damaged household capital to the related sectors; thirdly, it offers several sensitivity methods with which to analyse various alternative scenarios through the Flood Footprint Model. In addition, this study supports the idea that either key sectors or industries that are sensitive to the total flood footprint within an economy can be identified through a flood footprint assessment. Thus, in the post-flood period, policy-makers and/or relevant stakeholders need to draw up recovery plans for both certain sectors and for the entire economy, based on various scenarios and then select the most effective recovery plan, according to the lowest flood footprint.

Chapter 6 Flood Footprint Model Illustration III: A Hypothetical Two-floods Event

This chapter applies the Flood Footprint Model to a hypothetical two-flood event. It details the process of calculating the indirect flood footprint calculation, applying the model to four types of flood scenarios, with various occurrence times, direct capital losses of the subsequent flood and different external assistance (import) conditions. Moreover, the threshold for flood-induced capital damage loss within a given economy is analysed.

6.1. Introduction

The regional direct economic impact can be extended in the following natural disasters; however, there is lack of evidence regarding the regional indirect economic impact of these events. For a more effective response in the future, it is therefore vital to carry out a complete risk analysis for multiple natural disasters. This section offers a way to analyse the indirect flood footprint of multiple- disasters based on a hypothetical case. In many regions, especially coastal, riverine or insular regions, natural disasters are typically multi-hazard. The focus in this chapter is two natural disasters occur in a given region during a certain period and only sudden-onset natural disasters are analysed (UNISDER, 2015).

The Flood Footprint Model is applied to a hypothetical numerical example to validate the applicability of the model for assessing the footprint of multi-hazard. The basic IO table for the hypothetical numerical example (Table 6.1) is retrieved from Schaffer (1999), which in turn is aggregated from a detailed economic table for Georgia in 1970. The original table shows the transactions among 50 industries, 6 final-payments and 6 final-demand sectors, while the new hypothetical table only focuses on five broad industries and three final consumers.

Table 6.1 Input-output table of the hypothetical numerical example. (Unit: million USD/year)

To / From	Extraction	Construction	Manufacturing	Trade	Services	Household expenditures	Other final demand	exports	Total demand
Extraction	183	31	599	6	73	99	88	596	1674
Construction	14	1	43	14	293	0	1803	353	2520
Manufacturing	142	414	1390	110	356	1275	1130	9344	14162
Trade	52	224	520	72	257	2563	161	970	4820
Services	102	221	862	558	1990	4262	523	2828	11347
Households	595	665	3696	2385	4603				
Other payments	261	191	1624	1365	2402				
Imports	325	773	5428	311	1372				
Total inputs	1674	2520	14162	4820	11347				

Due to the lack of data about this economic system, aside from the information provided in Table 6.1, other related data in this case are based on my own assumptions. The time unit for this case is weekly (1 year=52 weeks); the monetary value is U.S. dollar and its currency sign is USD; the monetary unit for the value data is one million USD. The occurrence time of the first event here is assumed to be time 0, and recovery begins the following week, namely Week 1. With regards to the subsequent event, the occurrence time is m and from the time (m+1), it begins to recover from the combined influences caused by the first and second natural disasters.

This economic system is assumed to be subjected to two floods that lead to the same physical influences. In other words, both floods destroy the 20% industrial capital of each sector and damage 0.05% of household capital, and nearly 10% of the labour force is affected. The subsequent natural disaster occurs one week after the first, which means that the subsequent natural disaster attacks the regional economy in the second week (m=2). As the recovery path of labour productivity is an exogenous parameter in the Flood Footprint Model, this case assumes that in each week half of the remaining damaged labour productivity from previous week is restored. For example, a natural disaster immediately affects 10% of labour production, of which 5% (half of 10%) can be restored during the first week and in the second week, there is a further 2.5% (half of 5%) recovery. Meanwhile, it is assumed that when the damage fraction of labour productivity is under 2%, the labour capacity in following week is able to be fully restored. Based on the industrial capital stock distribution of the Beijing economy, the industrial capital stock for each sector is assumed as $\mathbf{s_{cap}^0} = \begin{bmatrix} 150 \\ 100 \\ 500 \\ 2000 \\ 4000 \end{bmatrix}$ and the household capital stock is 3600 million USD. The basic demand for each sector is equal to its household expenditures and neither production nor services from the construction sector are consumed as a basic demand.

6.2. Application of Flood Footprint Model

6.2.1. Data

The domestic coefficient $\mathbf{A}$ come from Table 6.1 is

$\begin{bmatrix} 0.1093 & 0.0123 & 0.0423 & 0.0012 & 0.0064 \\ 0.0084 & 0.0004 & 0.0030 & 0.0029 & 0.0258 \\ 0.0848 & 0.1643 & 0.0981 & 0.0228 & 0.0314 \\ 0.0311 & 0.0889 & 0.0367 & 0.0149 & 0.0226 \\ 0.0609 & 0.0877 & 0.0609 & 0.1158 & 0.1754 \end{bmatrix}$. Since the data offered in Table 6.1 is annual base, at weekly level, total output $\mathbf{x^0} = \begin{bmatrix} 32 \\ 48 \\ 272 \\ 93 \\ 218 \end{bmatrix}$, total final demand $\mathbf{f^0} = \begin{bmatrix} 15 \\ 41 \\ 226 \\ 71 \\ 146 \end{bmatrix}$, maximum import capacity $\mathbf{y_{imp}^0} = [6 \;\; 15 \;\; 104 \;\; 6 \;\; 26]$, household expenditures $\mathbf{f^0} = \begin{bmatrix} 2 \\ 0 \\ 25 \\ 49 \\ 82 \end{bmatrix}$ and other final demand $\mathbf{f_{others}}^{\mathbf{0}} = \begin{bmatrix} 13 \\ 41 \\ 201 \\ 22 \\ 64 \end{bmatrix}$, the basic demand $\mathbf{f_{cd}^t} = \begin{bmatrix} 2 \\ 0 \\ 25 \\ 49 \\ 82 \end{bmatrix}$. Capital damage fractions caused by the first ($\boldsymbol{\alpha}$) and second event ($\boldsymbol{\alpha}_2^0$) are same, $\boldsymbol{\alpha}_1 = \boldsymbol{\alpha}_2^0 = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{bmatrix}$, reduced labour productivity fractions of the two disasters are also same as $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_2^0 = \begin{bmatrix} 0.1 \\ 0.1 \\ 0.1 \\ 0.1 \\ 0.1 \end{bmatrix}$ ($\boldsymbol{\beta}_1$ is for the first disaster, and $\boldsymbol{\beta}_2^0$ stands for the subsequent disaster). Meantime, 50% of the household damaged capital allocates to Construction sector, and 40% goes to Manufacturing that refers to energy and products support, the last 10% distributes to Services.

6.2.2. Recovery from the First Flood

Before other shocks on the regional economy, the recovery process of the first natural disaster is according to the single natural disaster restoration that is presented in Section 3.2.2. Due to the disruption of this disaster, recovery demand that contains both industrial and household damaged capital is

$$\left.\begin{array}{r} \mathbf{f_{ID}} = \hat{\boldsymbol{\alpha}} \times \mathbf{s_{cap}^0} = \begin{bmatrix} 30 \\ 20 \\ 100 \\ 400 \\ 800 \end{bmatrix} \\ \mathbf{f_{HD}} = \begin{bmatrix} 0 \\ 0.90 \\ 0.72 \\ 0 \\ 0.18 \end{bmatrix} \end{array}\right\} \mathbf{f_{rec}} = \mathbf{f_{ID}} + \mathbf{f_{HD}} = \begin{bmatrix} 30 \\ 21 \\ 101 \\ 400 \\ 800 \end{bmatrix} \qquad (3.70).$$

The total final demand after the first event becomes

$$\mathbf{f_d} = \mathbf{f^0} + \mathbf{f_{rec}} = \begin{bmatrix} 45 \\ 62 \\ 327 \\ 471 \\ 947 \end{bmatrix} \quad (6.1);$$

the total required industrial demand is

$$\mathbf{x_d} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f_d} = \begin{bmatrix} 83 \\ 99 \\ 446 \\ 536 \\ 1272 \end{bmatrix} \quad (6.2).$$

Available production is

$$\left.\begin{aligned} \mathbf{x^1_{cap}} &= \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_1}^1\right)\mathbf{x^0} = \begin{bmatrix} 26 \\ 29 \\ 218 \\ 74 \\ 175 \end{bmatrix} \\ \mathbf{x^1_{lab}} &= \left(\mathbf{I} - \widehat{\boldsymbol{\beta}_1}^1\right)\mathbf{x^0} = \begin{bmatrix} 29 \\ 44 \\ 245 \\ 83 \\ 196 \end{bmatrix} \end{aligned}\right\} \mathbf{x^1} = \min(\mathbf{x^1_{cap}}, \mathbf{x^1_{lab}}) = \begin{bmatrix} 26 \\ 39 \\ 218 \\ 74 \\ 172 \end{bmatrix} \quad (6.3),$$

Imports depend on the damaged condition of transport system that belongs to the Services sector, so the imports are

$$\mathbf{y^1_{imp}} = (1 - \alpha^1_{services})\mathbf{y^0_{imp}} = [5 \;\; 12 \;\; 84 \;\; 5 \;\; 21] \quad (3.76).$$

Because at this moment, $\mathbf{Ax^0} + \mathbf{f^1_{cd}} < x^1 + \mathbf{y^1_{imp}} \leq \mathbf{Ax^0} + \mathbf{f^1_{cd}} + \mathbf{f_{rec}}$ (3.106), come into Scenarios 2.1.

In the first week

Besides the intermediate demand and basic demand, the remaining production ($\mathbf{f^t_{new}}$) is

$$\mathbf{f^1_{new}} = \min\left(\mathbf{x^1} + \mathbf{y^1_{imp}}, \mathbf{x^0} + \mathbf{y^0_{imp}}\right) - \mathbf{Ax^0} - \mathbf{f^1_{cd}} = \begin{bmatrix} 12 \\ 44 \\ 230 \\ 8 \\ 42 \end{bmatrix} \quad (3.107),$$

and recovered capital during this week is

$$\mathbf{f^1_{rec}} = \min(\mathbf{f_{rec}}, \mathbf{f^1_{new}}) = \begin{bmatrix} 12 \\ 21 \\ 101 \\ 8 \\ 42 \end{bmatrix} \quad (3.108).$$

Remaining recovery demand for next week is

$$\mathbf{f}^{\mathbf{2}}_{\mathbf{rec\_rem}} = \mathbf{f}_{\mathbf{rec}} - \mathbf{f}^{\mathbf{1}}_{\mathbf{rec}} = \begin{bmatrix} 18 \\ 0 \\ 0 \\ 392 \\ 758 \end{bmatrix} \quad (6.4),$$

and damage fraction of capital for the second week is

$$\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{2}} = (\mathbf{f}_{\mathbf{rec}} - \mathbf{f}^{\mathbf{1}}_{\mathbf{rec}})./\mathbf{s}^{\mathbf{0}}_{\mathbf{cap}} = \begin{bmatrix} 0.12 \\ 0 \\ 0 \\ 0.19 \\ 0.19 \end{bmatrix} \quad (3.110).$$

In the second week, the same reconstruction process is modelled as in the first week, recovered damaged capital is

$$\mathbf{f}^{\mathbf{2}}_{\mathbf{rec}} = \min(\mathbf{f}_{\mathbf{rec}}, \mathbf{f}^{\mathbf{2}}_{\mathbf{new}}\ ) = \begin{bmatrix} 14 \\ 0 \\ 0 \\ 8 \\ 44 \end{bmatrix} \quad (6.5),$$

and remaining recovery demand for the third week is

$$\mathbf{f}^{\mathbf{3}}_{\mathbf{rec\_rem}} = \mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{\mathbf{2}} \mathbf{f}^{k}_{\mathbf{rec}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 384 \\ 754 \end{bmatrix} \quad (6.6),$$

The damage fraction of the third week is $\boldsymbol{\alpha}_{\mathbf{1}}{}^{\mathbf{3}} = \begin{bmatrix} 0.03 \\ 0 \\ 0 \\ 0.19 \\ 0.18 \end{bmatrix}$.

6.2.3. Recovery from the Subsequent Flood

The subsequent flooding occurred in the second week (m=2). Hence, influenced of this disaster on the economic system is starting from the third week; meantime, the restoration of economy is changed from the single disaster rebuild to multiple disasters restored.

Thus, **in the third week**, the increased damaged capital caused by the second shock is same as the first disaster,

$$\mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}} = \begin{bmatrix} 30 \\ 21 \\ 101 \\ 400 \\ 800 \end{bmatrix}.$$

New recovery demand for the third week is

$$\mathbf{f}_{\mathbf{rec\_rem}}^{\mathbf{m+1}} = (\mathbf{f}_{\mathbf{rec}} - \sum_{k=1}^{m} \mathbf{f}_{\mathbf{rec}}^{\mathbf{t}k}) + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}} = \mathbf{f}_{\mathbf{rec\_rem}}^{\mathbf{3}} = \begin{bmatrix} 34 \\ 21 \\ 101 \\ 784 \\ 1514 \end{bmatrix} \text{ (m=2)} \quad (3.123),$$

Damage fraction for this week increased as

$$\boldsymbol{\alpha}_{\mathbf{2}}{}^{\mathbf{3}} = \left(\left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}}\right) - \sum_{k=1}^{\mathbf{2}} \mathbf{f}_{\mathbf{rec}}^{k}\right)./\mathbf{s}_{\mathbf{cap}}^{\mathbf{0}} = \begin{bmatrix} 0.23 \\ 0.2 \\ 0.2 \\ 0.39 \\ 0.38 \end{bmatrix} \quad (6.7),$$

and capital production is

$$\mathbf{x}_{\mathbf{cap}}^{\mathbf{3}} = \left(\mathbf{I} - \widehat{\boldsymbol{\alpha}_{\mathbf{2}}}^{3}\right)\mathbf{x}^{\mathbf{0}} = \begin{bmatrix} 25 \\ 39 \\ 218 \\ 56 \\ 136 \end{bmatrix} \quad (6.8).$$

If we calculate $\boldsymbol{\alpha}_{\mathbf{2}}^{\mathbf{3}}$ through Eq.66,

$$\boldsymbol{\alpha}_{\mathbf{2}}{}^{3} = \boldsymbol{\alpha}_{\mathbf{1}}{}^{3} + \boldsymbol{\alpha}_{\mathbf{2}}{}^{0} = \begin{bmatrix} 0.03 \\ 0 \\ 0 \\ 0.19 \\ 0.18 \end{bmatrix} + \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{bmatrix} = \begin{bmatrix} 0.23 \\ 0.2 \\ 0.2 \\ 0.39 \\ 0.38 \end{bmatrix} \quad (6.9).$$

Either from logical method (Eq.3.128) or mathematical approach (Eq.3.125), the influence on capital productivity caused by the subsequent flood is same.

For labour constraints, labour damage fractions and labour production become

$$\boldsymbol{\beta_2}^{\mathbf{3}} = \boldsymbol{\beta_1}^{\mathbf{3}} + \boldsymbol{\beta_2}^{\mathbf{0}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0.16 \\ 0.10 \end{bmatrix} + \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \\ 0.36 \\ 0.3 \end{bmatrix} \quad (3.131),$$

$$\mathbf{x}_{\mathbf{lab}}^{\mathbf{t}} = \left(\mathbf{I} - \widehat{\boldsymbol{\beta_2}}^{t}\right)\mathbf{x}^{\mathbf{0}} = \begin{bmatrix} 28 \\ 42 \\ 238 \\ 81 \\ 191 \end{bmatrix} \quad (3.133).$$

While, imports are

$$\mathbf{y}_{\mathbf{imp}}^{\mathbf{3}} = \left(1 - \alpha_{2\_tran}^{3}\right)\mathbf{y}_{\mathbf{imp}}^{\mathbf{0}} = \begin{bmatrix} 4 \\ 9 \\ 65 \\ 4 \\ 16 \end{bmatrix} \quad (3.135).$$

At this time,

$$\mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{3}} < x^{3} + \mathbf{y}_{\mathbf{imp}}^{\mathbf{3}} \leq \mathbf{Ax}^{\mathbf{0}} + \mathbf{f}_{\mathbf{cd}}^{\mathbf{3}} + \left(\mathbf{f}_{\mathbf{rec}} + \mathbf{f}_{\mathbf{rec2}}^{\mathbf{0}} - \sum_{k=1}^{2} \mathbf{f}_{\mathbf{rec}}^{k}\right) \quad (3.136),$$

the recovery process come into Scenarios 2.1.

Until in the 75th week, is industrial productivity full restored and the affected economic system completely recovered to pre-disaster level. This means that in this case, at least 74 weeks are spent on reconstruction of the damaged economic system, and the flood footprint is 11838 million USD.

$$\left.\begin{aligned} \mathbf{x}_{\mathbf{direct}} &= \begin{bmatrix} 60 \\ 42 \\ 202 \\ 800 \\ 1600 \end{bmatrix} \\ \mathbf{x}_{\mathbf{indirect}} &= \begin{bmatrix} 151 \\ 324 \\ 2238 \\ 1532 \\ 4888 \end{bmatrix} \end{aligned}\right\} x_{total} = x_{direct} + x_{indirect} = 11838 \quad (3.121)$$

6.3. Results

As calculated above, the total flood footprint resulted from two floods in the hypothetical case is estimated as 11838 million USD through the Flood Footprint Model. The direct flood footprint is 2704 million USD, nearly a 23% share of the total flood footprint; while the other 77% is from the indirect footprint, about 3.38 times higher than the direct one, amounting to 9134 million USD. Among the five sectors, the services sector accounts for 54% of the total flood footprint, with 6488 million USD, followed by the trade and manufacturing sectors, both with a 20% share of the flood footprint. Extraction has the smallest percentage, only 1.8%. Meanwhile, 74 weeks, almost 1.4 years are needed to restore the economic transaction among sectors.

The direct flood footprint of multiple natural disasters consists of direct economic loss from every flood event, and in this case, the direct value of each event is 1350 million USD, since the two floods are assumed to result in the same direct impacts on the economic system. However, calculating the indirect impact of multiple events involves not simply adding up all the indirect cost caused by each shock, due to the indirect combined influence of multiple natural hazards. Taking this case as an example, if the subsequent event does not occur, the first flooding as an individual shock to the regional economy requires 26 weeks for completely recovery and leads to 2336 million USD flood footprint. In particular, direct loss will be 1352 million USD from while the indirect flood footprint is another 984 million USD. When regarding this multiple case as two individual shocks and calculating their respective impact separately, the total indirect flood footprint is only 1968 million USD, which is 8150 million USD less than the actual amount; thus the total flood footprint decreases to 4672 million USD.

Figure 6.1 presents the recovery processes for the single and multiple (two) natural disasters in the hypothetical numerical example. The restoration for production capacity, recovery demand and indirect flood footprint of a single disaster (Figure 6.1a,b,c) show continuing trends, while multiple disasters (Figure 6.1d,e,f) present dynamic tendencies. In Figure 6.1a and 6.1d, the blue lines that indicate industrial production capacity are closer to the green lines (capital production capacity), demonstrating that damaged capital induces lower production and has a greater impact on the available production capacity.

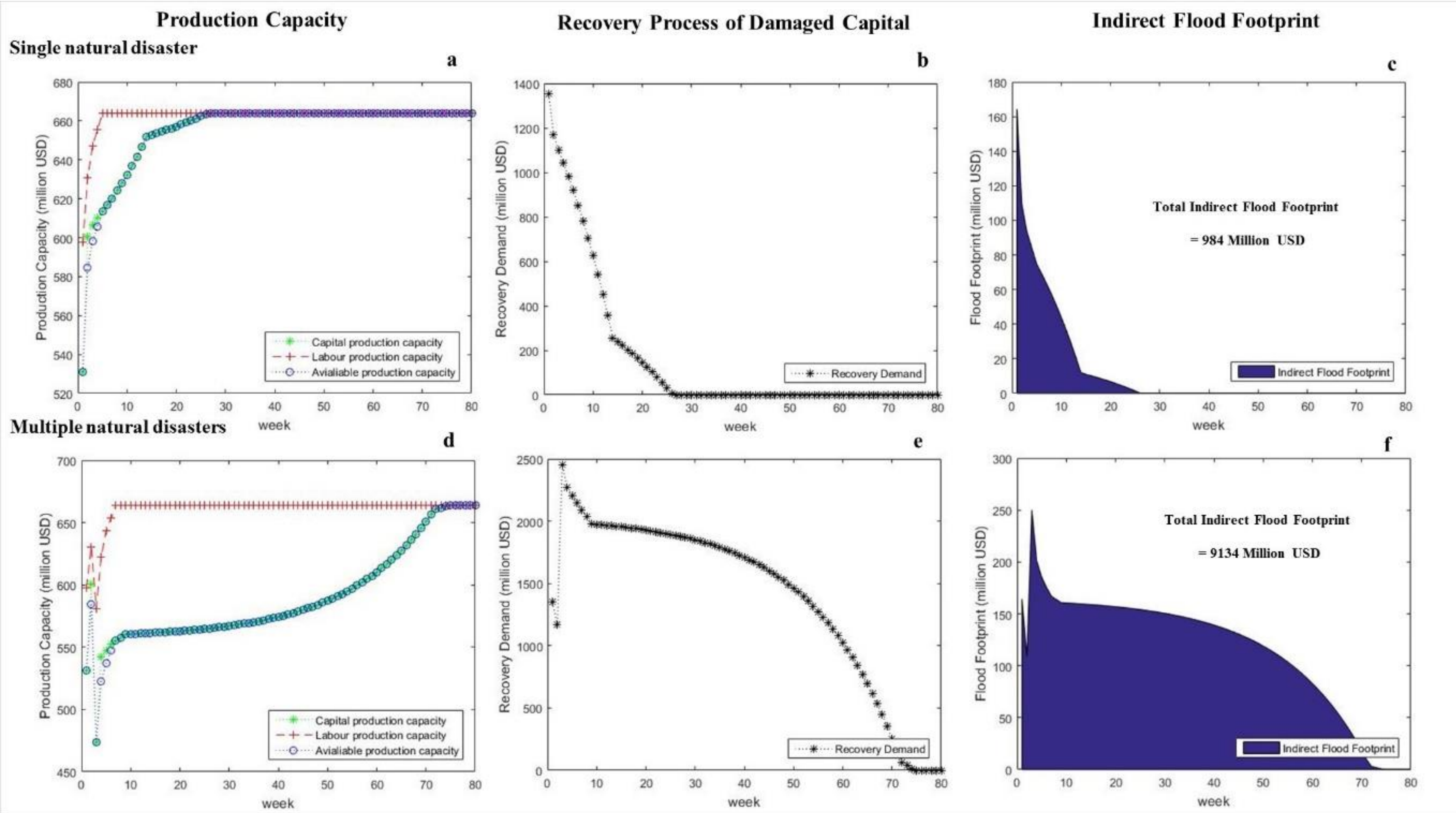


Figure 6.1. *Recovery process of the hypothetical numerical example. Chart a, b ,c shows the conditions of single flooding recovery, and other three chart d, e and f present the recovery trends for multiple (two) floods.*

Due to disruption of the subsequent event that occurs in the second week, the rebuilding process enters into a new stage from the third week by incorporating the damage caused by the subsequent disaster. Consequently, production capacity (Figure 6.1d), integrating both labour and capital limitations, shows an increasing trend during the entire restoration process, with the lowest point in the third week. Meanwhile, recovery demand (Figure 6.1e) displays a falling tendency with the highest amount in Week 3. When we consider the indirect flood footprints of multiple events (Figure 6.1f), it is clear that during the first two weeks, the economic system is concentrated on addressing the damage caused by the first shock; the following 16 weeks is used to recover the combined impact of the two disasters. The highest point in the third week is 200 million USD larger than the second highest point in the first week, due to the cumulative effect, because when the subsequent disaster hits the economy, the damaged capital and labour resulting from the previous event has not recovered yet. It is important to clarify that the estimation approaches towards calculating the flood footprint results from the multiple floods are different. Only under the condition that the following disaster occurs after full restoration of the first disaster, will the total flood footprint equal to the sum of the separate flood footprints. Otherwise, flood footprints induced by multi-hazard are more serious than for multiple individual events.

6.4. Sensitivity Analysis

Although the outcomes from the Flood Footprint Model in this case are sensitive to the model inputs and external assumptions, sensitivity analyses for various scenarios incorporating different model parameters, such as the alternative ability of labour recovery and different reconstruction plans of damaged capital, are proposed in the previous single-disaster cases (Chapter 4.3 and 5.4). However, compared with the single flood, in multiple events, more attention needs to be directed towards the adaptive resilience of the regional economy. It seems that total economic impact and speed of recovery of the affected economy are likely to be significantly influenced by the type and severity of the subsequent disaster. Due to lack of focus in previous research on analysing the indirect economic impact of multiple floods, this section offers a series of scenario analyses through the Flood Footprint Model that show how the multi-hazard disasters influence the total economic impact. The multi-hazard case calculations from Chapter 6.2 and 6.3 is regarded as the Base Scenario, and the input factors used are the basic conditions of this scenario.

6.4.1. Various Occurrence Times for the Subsequent Flood

As the time unit for flood footprint assessment in this case is weekly, the occurrence time of the flood here is not a specific point in time, but rather, indicates the week in which the disaster affected the economic system. In the case of Hurricane Katrina (2005), the massive flooding due to levee breaches submerged 80% of New Orleans city (United States) after the hurricane hit (WIKIPEDIA, 2005). The time gap between these two disasters is less than one week and the first week is the occurrence time for the hurricane-induced flooding. In the case of the three hurricanes that hit the United States in 2017, on August 24th, September 10th and September 20th, respectively (WIKIPEDIA, 2017a, WIKIPEDIA, 2017c, WIKIPEDIA, 2017b), the first hurricane, Harvey, is assumed as Week 0, while Irma and Maria occur in Week 2 and 4. As it is difficult to predict when the subsequent flood will occur and disrupt the regional economy transaction, in order to discuss how this factor impacts the economy, seven scenarios are shown in Table 2 with occurrence times of the successive events from the first to the seventh week (Scenarios T1-T6). All the scenarios include two independent floods and apart from the timing of the subsequent event, other basic conditions and inputs of Scenarios T1-T6 are same as for the Base scenario.

Table 6.2 provides the flood footprints of these scenarios. It is clear that Scenario T-1 results in the largest flood footprint, 17523 million USD, and is 2.7 times higher than the lowest one, 6588 million USD from Scenario T-6; this is followed by the Base Scenario, with 11838 million USD. The flood footprints for the others are lower than 10000 million USD. Regarding the indirect flood footprint, T-1 leads to the largest indirect footprint, over 85% of its total flood footprint, 14819 million USD, and this number equals to 3.8 times the indirect flood footprint caused by T-6, which is only 3884 million USD. Regardless of scenario, the direct economic loss in each situation is the same, 2700 million USD, since both independent events lead to the same physical and labour damage. The impact of the two-flood disaster on the economy, especially the indirect impact, changes according to the occurrence of the subsequent disaster (*m*). When *m* increases from week one to week seven, the indirect flood footprint decreases from 14819 to 3884 million USD, and the percentages attributable to the indirect footprint also decreases from 85% to 59%. Meanwhile, there is no evidence that *m* has any influence on the recovery period. For example, the *m* gap between Base and T-4 is 3 weeks, and the indirect flood footprint of the latter is only 57% of the former scenario, but in both scenarios, the economy requires 74 weeks to recover.

Table 6.2 Flood footprints under different scenarios that refers to the various occurrence times of the subsequent flood.

Scenario	*m* (week)	Recovery Period (week)	Indirect Flood footprint (million USD)	Total Flood Footprint (million USD)	Percentage of Indirect flood footprint
Base	2	74	9134	11838	77%
T-1	1	114	14819	17523	85%
T-2	3	65	6695	9399	71%
T-3	4	86	6319	9023	70%
T-4	5	74	5197	7901	66%
T-5	6	66	4446	7150	62%
T-6	7	61	3884	6588	59%

Notes: '*m*' stands for the occurrences time of the subsequent flood.

Figure 6.2 and 6.3 illustrate how *m* influences the recovery process in each scenario. Base Scenario, T-1 and T-3 are Type 1s as introduced in Chapter 3.2.3:"When the subsequent disaster shocks the economic system, both damaged capital and affected labour productivity due to the first disaster are in recovery". The other two scenarios (T-5 and T-6) are Type 2s: "industrial capital is in a process of reconstruction and labour has already completely recovered". It seems that in the Type 1 scenarios, either labour (red line) or capital capacity lines (green line) contain one lowest point. This point indicates that the constraints caused by the subsequent event has already been added into the whole recovery process and from this week, the economy starts to recover from the combined effect of the first and second shocks. With

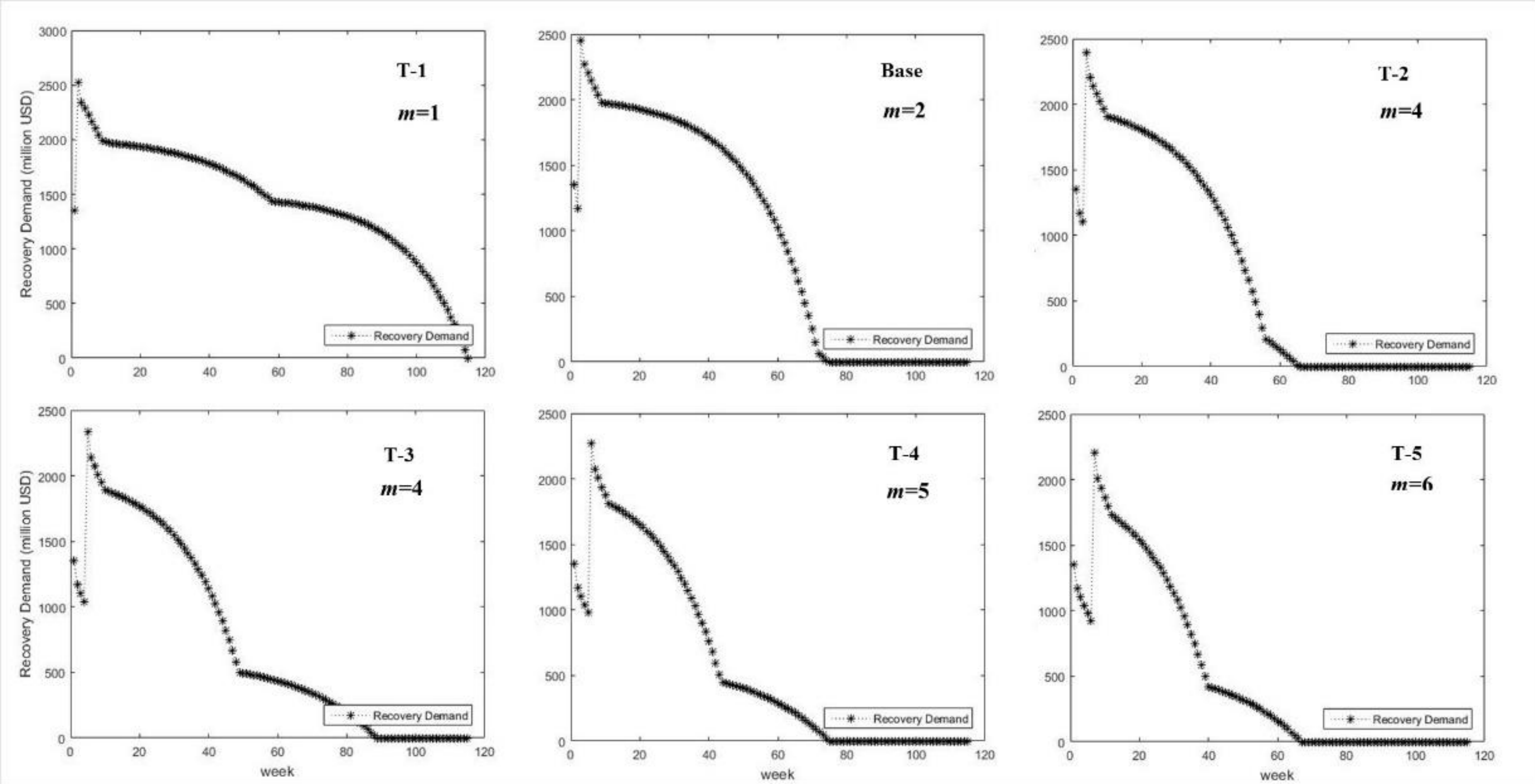


Figure 6.2. Recovery demand trends of scenarios that contain different occurrence times for the subsequent flood.

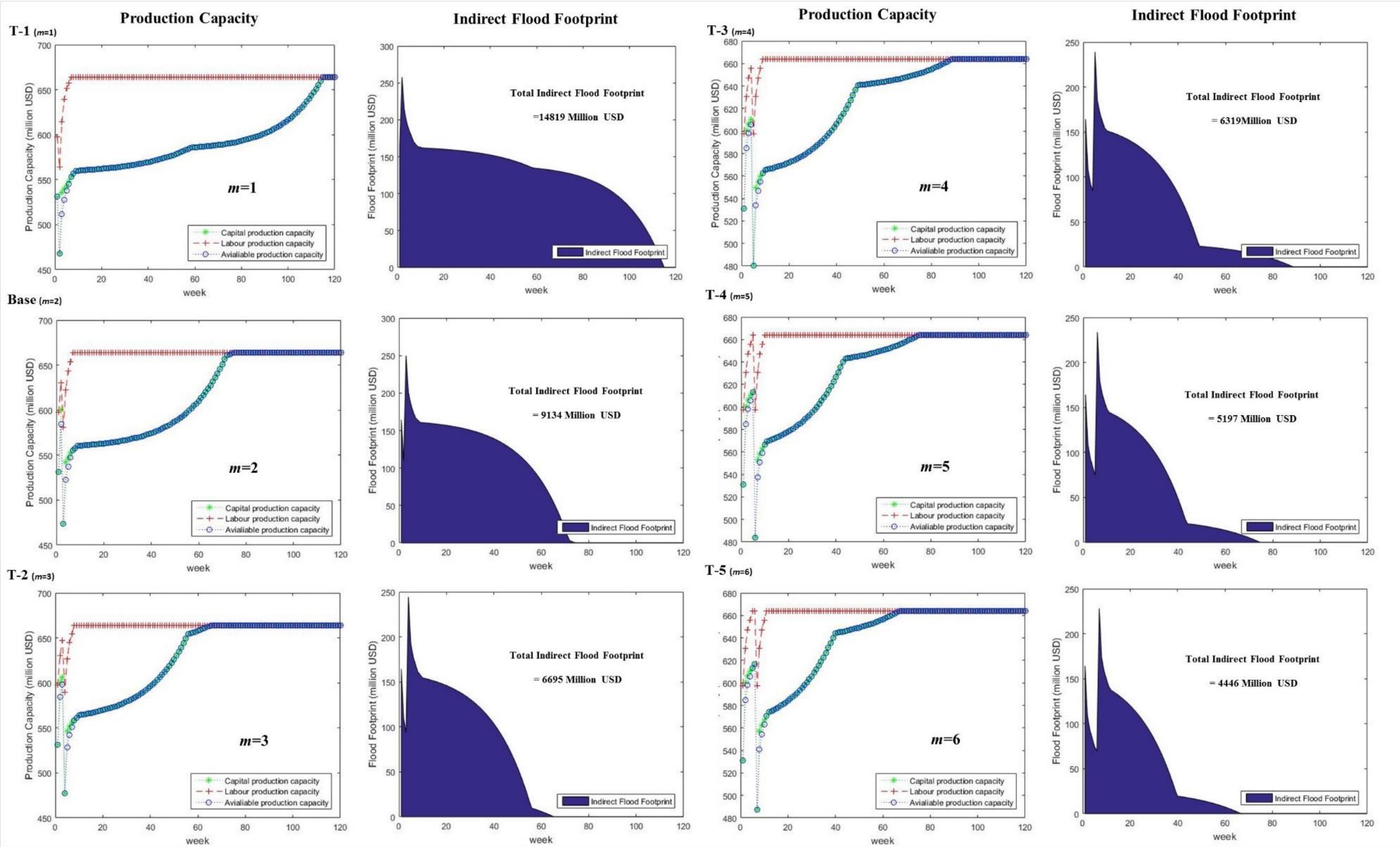


Figure 6.3. *Recovery processes for production and indirect flood footprint under scenarios that contains different occurrence times for the subsequent flood (m).*

Type 2, it is clear that the two lowest points same in the red lines are the same, mainly because both disasters lead to the same labour constraints, and at the time of the second point, affected labour from the first shock has already been restored. As the recovery of labour capacity is an exogenous factor, its point in each week is decided by external decisions. In terms of capital capacity, it depends significantly on the recovering process as modelled by the Flood Footprint Model and for this reason, both capital capacity (Figure 6.3) and recovery demand show various trends (Figure 6.2) in each scenario. In addition, since the recovery speed of labour productivity is faster than the recovery of capital productivity, total production capacity is entirely limited by damaged capital and this is the reason why the blue and green lines coincide with each other after labour productivity returns to its pre-disaster level. When we look at the indirect flood footprint trends, the peak point in each scenario divides the recovery process into two parts: before the peak point is recovery from the first disaster and after this point is the reconstruction with the combined constraints of the two disasters. Moreover, it is worth noting that under the conditions of Type 1 and 2, if both disasters lead to the same degree of direct damage on the same region, the shorter the gap between the occurrence times of the two disasters (this gap must be larger than 0) the larger the gap between the total and indirect flood footprints .

6.4.2. Alternative Direct Capital Loss caused by Successive Events

Direct economic loss of regional capital is an essential component in assessing flood footprint as it determines the post-disaster recovery demand and available capital production capacity. Generally, the capital damaged by a disaster is primarily related to the capital distributions of the affected region and the intensity of the natural disaster itself. Regarding multiple disasters, there is no data or evidence to reveal any relevance for capital loss between the first and the subsequent disaster. For instance, Typhoon Hato led to direct economic losses of 1.79 billion USD (nearly 0.07% of Guandong capital stock) in Guandong province, China on Aug 23rd 2017; four days later, Typhoon Pakhar made landfall over southern China and the direct loss in Guangdong was only 436 million USD, 1.35 billion USD less than Hato (WIKIPEDIA, 2017d, SinaNews, 2017). Another example is Hurricane Katrina, an extremely destructive tropical cyclone that hit the United States during August 2005 (WIKIPEDIA, 2005). New Orleans was the most damaged cite after this hurricane, with over 150 billion USD direct economic damage.

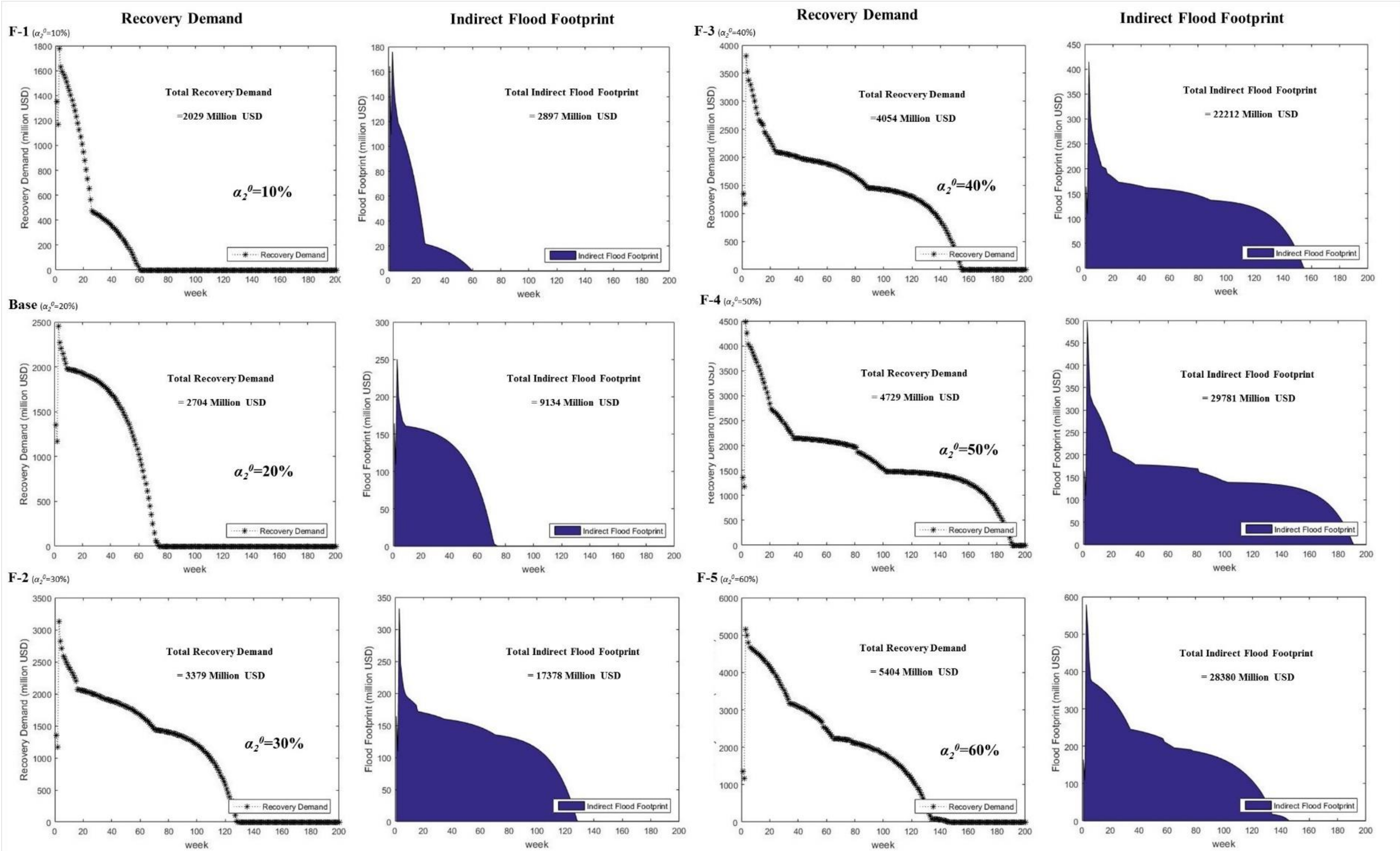
Since it not only faced the attack from this deadly storm, but also suffered a series of disasters followed with Hurricane Katrina, especially for the hurricane-induced flooding, which accounts for nearly half of the total economic damage of Katrina (Boettke et al., 2007, WIKIPEDIA, 2005, BBC, 2014, Amadeo, 2018)

Therefore, to better understand the impact of direct capital damage on the regional economic system, seven scenarios are created for damage caused by the subsequent disaster, represented as different capital damage fractions (α_2^0) (Table 6.3), while other inputs remain the same as those in the Base Scenario. This means that in all scenarios, both disasters lead to the same capital damage fraction of the five sectors: for the first disaster the number is 20% and for the subsequent, equal to α_2^0.

Table 6.3 Indirect flood footprints under different capital damage fractions by the subsequent flood.

Scenario	α_2^0	Recovery Period (week)	Direct Flood footprint (million USD)	Indirect Flood footprint (million USD)	Total Flood Footprint (million USD)
Base	20%	74	2704	9134	11838
F-1	10%	60	2029	2897	4926
F-2	30%	128	3379	17378	20757
F-3	40%	154	4054	22212	26266
F-4	50%	190	4729	29781	34510
F-5	60%	146	5404	28380	33784
F-6	70%	-	-	-	-

Notes: 'α_2^0' is the industrial capital damage fraction that directly caused by the subsequent flood.



Notes: '$\alpha_2{}^0$'is the industrial capital damage fraction that directly caused by the subsequent flood.

Figure 6.4. Recovery processes for recovery demand and indirect flood footprint under scenarios with different direct capital loss from the subsequent flood.

As shown in Table 6.3, when α_2^0 is 70%, this economic system will never return to pre-disaster levels because the capital production capacity is so small that recovery demands for the Extraction and Trade sectors will never be fully rebuilt and the regional economic transaction is not able to recover to pre-disaster levels. Scenario F-1 with 10% of α_2^0 requires the shortest recovery time (60 weeks) and leads to the lowest flood footprint with 4926 million USD, only 14% of the largest one in F-4, of 34510 million USD. F-5 accounts for the largest direct flood footprint (5404 million USD), and it is clear that the direct flood footprint increases along with an increasing α_2^0, because the direct flood footprint is assumed to be the same amount of direct capital loss in this study.

However, the indirect flood footprint does not correspond to the tendency of the direct footprint: the highest indirect flood footprint is generated by Scenario F-4, which is also the scenario that takes the longest to completely recover (190 weeks). Since in the Flood Footprint Model, the modelling process varies according to the different conditions of available production and the remaining recovery demand in each week, the indirect flood footprint does not simply rely on the direct economic loss but is modelled by considering several factors, as mentioned in Chapter 4.3. It also explains the dynamic trends of recovery demands and indirect flood footprints in each scenario that are presented in Figure 6.4. The left side of the figure shows the recovery demand tendencies; the peak points of the black lines indicate the amount that includes the recovery demand resulting from the second event. Direct capital loss determines total regional recovery demand, but when considering the recovery process in detail, the recovery demand for each week depends on the reconstruction in the previous week. Thus, weekly repaired capital is also modelled through the Flood Footprint Model and various reallocations of production lead to different abilities to recover damaged capital each week. Thanks to internal impact between parameters in the Flood Footprint Model, both recovery demand or regional indirect flood footprint has their own dynamic features.

6.4.3. Regional Threshold for Damaged Capital of Floods

The adaptive resilience of an economy after a flood refers to the regional ability in the aftermath of a disruption to build upon new arrangements on production and services reallocation for recovering functionality to pre-disaster level (Rose and Krausmann, 2013). In this study, the regional adaptive resilience specifically refers to the ability to make the redistribution of remaining production that is constrained by damaged labour and capital. Meanwhile, in order to satisfy the given demand that takes basic demand and recovery demand into account during the rebuild period, imports are added as an external supplier with the maximum pre-disaster capacity.

However, with some extreme floods, the direct shocks on economic transactions damage the region beyond its adaptive resilience; in particular, the physical damage on property is too serious for functional recovery. As a result, it is not possible for an economic system to recover to its pre-disaster level. This was the case in Puerto Rico, United States, where Hurricane Maria destroyed over 80% energy during September 2017; the recovery foundation was estimated at 94.4 billion USD, which far exceeds the regional economic resilience. Puerto Rico had debts of more than 70 billion USD before the hurricane (Walsh, 2017, May 16) and this, added to the severity of the damage and lack of financial assistance (Galarza and Lee, 2017, November 19) severely hampered the recovery process. Taking this hypothetical two-flooding case as an example, this study proposes a link between damaged capital and regional adaptive resilience through the Flood Footprint Model. It should be pointed out that damaged capital here includes industrial and household affected capital, and only capital damage fractions change when compared with the Base Scenario.

This study defines the regional threshold for damaged capital as a range of fractions regarding capital damaged by floods that are suitable for regional adaptive resilience. In other words, a regional economy is able to completely recover under this threshold; conversely, if the data is out of the threshold, the damaged capital is so severe that the region is beyond its adaptive resilience. Since all five sectors are assumed to suffer the same damage fractions on capital as a result of the disaster, regional adaptive resilience is tested through several capital damage fractions of the first (α_1^0) and the subsequent events (α_2^0).

Table 6.4 Regional thresholds for the capital damage fraction caused by the floods.

Scenario	Threshold for capital damage fractions	
	First (α_1^0)[1]	Second (α_2^0)
Single flood	[0%, 65%][2]	-
Two floods	[0%, 10%]	[0%, 65%]
	[0%, 20%]	[0%, 62%]
	[0%, 30%]	[0%, 43%]
	[0%, 40%]	[0%, 29%]
	[0%, 50%]	[0%, 17%]
	[0%, 60%]	[0%, 5%]
	[0, 65%]	[0, 0.09%]

Notes:

1. 'α_1^0' is the industrial capital damage fraction that directly caused by the first flood, and 'α_2^0' is from the subsequent flood.

2. Data range of '[0%, 65%]' here indicate $0\% \leq \alpha_1^0 \leq 65\%$.

The results of thresholds on damaged capital for the economic system (Table 6.1) are displayed in Table 6.4. If a single natural hazard hits the economy, the acceptable range of damage fractions on regional capital are 0%-65%, which implies that when $\alpha_1^0 > 65\%$, the economic transaction caused by the first shock will never be restored to pre-disaster levels. In the case of two disasters, damaged capital thresholds on the subsequent flooding of seven groups with different α_1^0 are analysed separately. In the first group with α_1^0 is 0%-10%, the threshold for α_2^0 is 0%-65%, cause when $\alpha_1^0 = 10\%$, allowing a maximum α_2^0 is 65% and when the number exceeds 65%, the region will remain damaged. It is clear that along with the α_1^0 increases from 10% to 65%, the acceptable α_2^0 declines from 65% to 0.09%; meanwhile, through strengthening α_1^0 from range 0%-10% to 0%-65%, the threshold for α_2^0 is limited to 0%-65% to 0%-0.09%. The threshold for regional damaged capital is not only one specific data range, but includes several ranges according to different influencing factors, for example, damage level caused by the previous disaster and occurrence time for the subsequent event.

Furthermore, the critical sector in this regional economy is found to be the extraction sector, since the affected capital of this sector is unable to be restored when the data of α_2^0 is beyond the corresponding threshold, resulting in regional recovery being impossible.

6.4.4. Sensitivity to External Assistance

As an external supplier of production and services, imports offer more available production to a region. In the aftermath of a flood, there are three kinds of imports: the first is import production that is directly used as a substitution for domestic production; the second is the delivery of rescue and relief items for basic human demands such as food and water; the last is financial assistance utilized to purchase production or damaged equipment. This study primarily focuses on the influence of imports under the rationing scheme whereby basic and intermediate demands are the priority, followed by reconstruction and other final demands (as described in Chapter 4.3), regardless of import type.

Under the basic conditions that are used in the Base Scenario, the other three scenarios with different amounts of imports are compared below. Imports in Scenarios I-1, BASE, I-2 and I-3 are 0%, 50%, 100% and 200% of pre-disaster level, respectively. Several points should be noted here. The first is that the maximum import capacity is assumed to be equal to pre-disaster imports. Secondly, import is only limited by the damaged capital of the transportation system. Thirdly, although imports can raise the accessible production during the recovery stage, not all imports can be added to the available production due to the constraints of the region's maximum production capacity. Here the maximum acceptable production in each week equals to the total amount from domestic outcomes and imports before the disaster.

Table 6.5. Flood footprints of import scenarios.

Scenario	Import	Recovery Period (week)	Indirect Flood footprint (million USD)	Total Flood Footprint (million USD)	Percentage of Indirect flood footprint
Base	With imports	74	9134	11838	77%
I-1	Without import	178	12611	15315	82%

I-2	Half of imports	124	12235	14939	82%
I-3	Double imports	56	5268	7972	66%

Table 6.5 and Figure 6.5 show the results and recovery processes of the four scenarios. In this hypothetical case, the independence of the economic system is very strong as even without any import (Scenario I-1), this region is able to recover to pre-disaster conditions. When the imports increase from 50% (Scenario I-2) to 200% (Scenario I-3), the recovery period decreases from 178 weeks to 56 weeks and the indirect flood footprint decreases from 12611 to 5268 million USD. Through influencing recovery demand pertaining to industrial capital, more imports lead to a reduction in the time period within which to satisfy the recovery demand and recover capital productivity (Figure 6.5) among the four conditions. However, even if under these four scenarios, the relationship between imports and indirect flood footprint is clear, when imports plus remaining production exceed the maximum capacity of regional production, the percentages of imports that are used for recovery will be less and consequently, increased imports are not able to result in decreased flood footprint. Hence, only when available production that includes imports is smaller than the maximum capacity of regional production, can more imports lead to a shorter recovery period and a smaller indirect flood footprint.

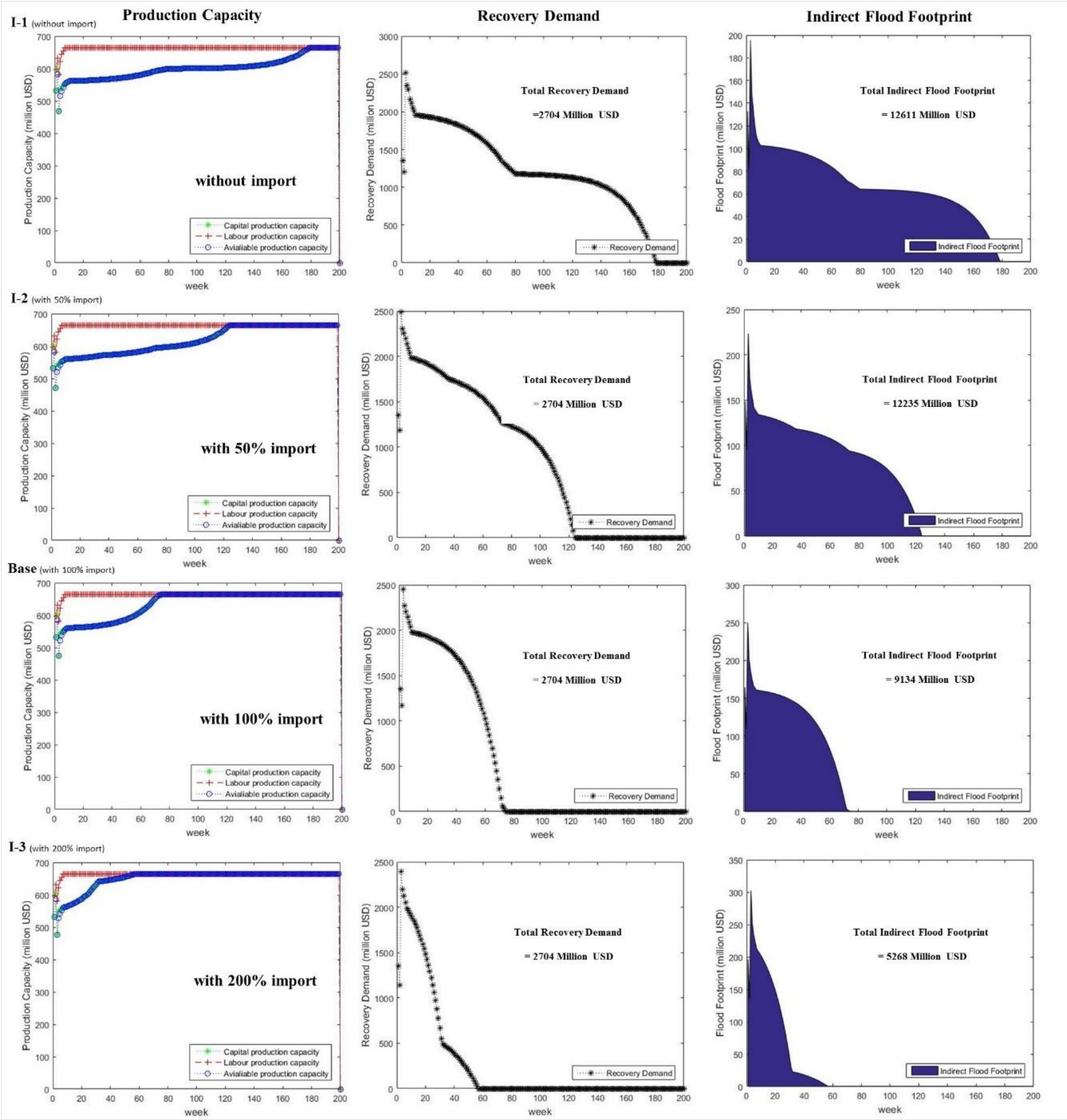


Figure 6.5. Recovery processes for different import scenarios.

6.1. Summary

Generally, multiple flood events have a greater impact on a regional economy than individual natural shocks due to the cumulative effect. However, there is a lack of research that analyzes the total economic impact resulting from multi-hazard disasters. To assess the indirect flood footprint of multiple floods more effectively, the Flood Footprint Model has been improved by building connections on the parameters of labour and capital between the first and subsequent flood. This is the first time that the Flood Footprint Model has been applied to the assessment of a multi-hazard flood footprint. On the basis of the hypothetical numerical example, this study proves that both from a mathematical and logical perspective, this model is an efficient and applicable method to analyse different types of multiple flood events and to clearly illustrate the range of recovery processes.

According to flood footprint analysis of the hypothetical example, several conclusions can be made. Firstly, the total flood footprint of multiple floods in a given region is larger than the sum of the flood footprint of each individual flooding, particular of the indirect flood footprint. In the hypothetical case, the flood footprint is 11838 million USD, which is 7076 million USD larger than the total flood footprint of each single disaster. The direct flood footprint of multiple floods is estimated as the total direct amount by each disaster due to it belonging to direct physical loss; but with regards to the indirect flood footprint, a multi-hazard disaster can lead to higher footprint due to the combined effect of these natural disasters. There is one condition in which the flood footprint equals to the total amount caused by each event. Under this condition, we can treat every event in the multiple disasters as individual events due to their independent recovery. Secondly, different occurrence times of the subsequent flood lead to various regional flood footprints in the case of multiple floods. Although this study focuses on two flood hazards that result in the same damage of physical assets and labour force, this conclusion holds for other kinds of multiple disasters. Through the sensitivity analysis on the time impact, it is found that if the subsequent flood disrupts the recovery of capital damaged by the first event, the shorter time gap between the occurrence times of the two disasters will result in a larger indirect flood footprint. Furthermore, higher direct damage cost of each disaster will result in a larger direct flood footprint of multi-hazard disasters, but a larger direct flood footprint does not mean the indirect flood footprint will be higher. By applying various parameters to the modelling process of the Flood Footprint Model, it is clear that the indirect flood footprint is not simply dependent on the direct economic impact. In addition, although imports can increase regional production and services, the influence of imports during the recovery process differs according to the constraint of maximum capacity of regional production.

Through new applications of the Flood Footprint Model, this chapter makes another important contribution, by identifying the regional or industrial thresholds for damaged capital in the case of multiple floods. It is easy to understand that if the damage caused by the disaster is too serious, the region will go beyond its adaptive resilience and the regional economy will not recover. However, what the Flood Footprint Model enables is to calculate the maximum acceptable damage level for the affected region, and the regional threshold for damaged capital from the first and the subsequent disasters. Furthermore, it also confirms which industries are critical to recovery since these specific sectors are sensitive to the capital damage fractions. The damage sustained by these critical sectors determines whether the economy can recover to its pre-disaster level.

Chapter 7 Conclusions

This thesis has explored a new way of assessing economic risk of flood-related disasters by adopting the concept of flood footprint and developing framework of flood footprint assessment. The study is largely inspired by previous contributions of natural disasters risk assessments and relevant approaches (Chapter 2 and 3). Two particular aspects of flood-induced economic consequences are the focus: firstly, establishing the indirect flood footprint and secondly, carrying out sensitivity analyses of post-flood economic recovery. Taking into account exogenous constraints within the affected economy due to single- or multiple (mainly two) flood disruptions, a Flood Footprint Model has been built to measure an indirect flood footprint (Chapter 3) and is successfully applied to three flood cases (as shown in Chapters 4-6). This chapter summarises the key findings, contributions and policy implications of this thesis. Limitations and suggestions for future research are outlined in the last section.

7.1. Concluding Remarks

Based on the work of this thesis, the three sub-questions that raised from Chapter 1.4.1 can be answered briefly through following explanations.

1) ***Which indicator is appropriate to express flood induced economic impacts?***

From a methodological point of view, the notion of flood footprint is confirmed to be a useful indicator to express the total economic consequences of flood disasters within a specific economic system, since it explains flood-induced economic consequences in a simple way and provides both location and time of each economic influence. Thus, flood footprint provides an easily way for people to understand the economic relationship between floods and human, and brings benefit to post-flood economic recovery and management.

2) ***What is the approach applied for flood footprint accounting with consideration to the production supply chains?***

As an alternative approach to the Input-output framework, the Flood Footprint Model is proved to possess flexibility and feasibility in indirect flood footprint accounting through the successful application of three flood cases (Chapter 4-6). This model is suitable for calculating the indirect flood footprint resulting from both single-flood and two-flood event. By capturing the inter-linkages of dependent sectors in a given economy, the Flood Footprint Model is able to simulate the likely imbalances in the economy in the aftermath of a flood event and illustrate the available productive capacity resulting from scarcity of input, i.e. the impact of physical damage and labour scarcity on industrial productivity. Thus, any supply bottleneck either among industries or between producers and consumers can be taken into account (Chapter 3).

3) ***How to assess the relevant factors influencing flood footprint within an economic system?***

Because flood footprints are sensitive to model parameters, the total flood footprint of a certain flood within a specific economy and the indirect flood footprint in particular, can be estimated with varying results. In other words, the same flood event may result in different flood footprints according to differences in variables. The Flood Footprint Model can provide a clear and detailed model of 'how the model parameters or external factors influence the post-flood economic condition. Based on sensitivity analysis (see Chapters 4-6), the following key points are made regarding the modelling process.

Firstly, during the post-flood period, critical constraints determine the available production of each sector. As the model only considers three factors that impact on industrial production capacity, which are labour productivity, capital productivity and the maximum productivity, the accessible production capacity is significantly constrained by the factor that has the largest influence. In other words, if the value of degraded capital productivity that is limited by damaged capital is the smallest when compared with the values of maximum productivity and degraded labour productivity limited by labour constraints, we can say that capital is the critical constraint and that accessible productivity largely relies on the degraded capital productivity. This also explains how capital and labour recovery plans affect the indirect flood footprint at every stage.

Secondly, the critical sectors in a certain economy define the required time for recovery. The ways in which critical sectors impact on recovery time can be categorized into three types: damage degree, recovery ability and recovery plan. For instance, if the economy takes a long time to recover, the reason may be 1) the damaged parts of some sectors are too damaged to be restored; 2) the ability of some sectors to recover is too low; 3) the recovery plan determines a long recovery of some specific sectors. All these related sectors can be defined as critical sectors. **Next**, import contributes to the reconstruction process by adding the available production at each stage. Import can push economic recovery and strengthen an economy's ability to recover. However, there is still a lack of evidence to show whether imports can mitigate the indirect flood footprint or reduce recovery time. In addition, another exogenous factor, basic demand, influences the recovery by changing the available resources and allocation scheme in each period. In a two-flood case, the total and indirect flood footprints are also highly constrained by factors like occurrence time, physical damage caused by the subsequent flood.

Moreover, sensitivity analyses of delayed recovery scenarios, in terms of weak governance, such as lack of financial assistance or scarcity of imports due to damaged transportation, reveals that the recovery delay for either capital or labour, or both of them, the larger the total and indirect flood footprints and the longer the recovery period. The accumulated effect produced by long-standing indirect flood footprints within the delay period is used to explain this phenomenon. **Furthermore**, one type of economic resilience, the regional threshold for flood-induced damaged capital loss, can be provided through the Flood Footprint Model. It shows the threshold within which an economy is able to completely recover. If the capital loss is beyond this threshold, the economy will never be able to return to pre-disaster levels within the basic assumptions of the model.

Overall, in respect of the single- and two-flood induced flood footprint, we can conclude firstly, that in a specific flood disaster, the higher direct flood footprint does not mean a higher indirect flood footprint because the indirect impact values are determined by inter-linkages among industries. Likewise, in multi-flood case, larger direct damage cost of each disaster will result in a larger direct flood footprint, but does not mean the indirect flood footprint will be higher. Secondly, in the case of a two-flood event, the total flood footprint within a given region is larger than the sum of the individual flood footprints, particularly of the indirect flood footprints.

Aside from applying the model to two hypothetical cases, the Flood Footprint Model is successfully applied to a real single-flood case, the 2012 Beijing 721 urban flooding that affected 1.9 million people and resulted in 11.64 billion CNY direct economic loss (Chapter 5). The total flood footprint of this disaster is calculated as 21.19 billion CNY, with a recovery period of 42 weeks, almost 1.18% of the total GDP in the Beijing area in the year 2012. In particular, the direct flood footprint was 11.64 billion CNY and the indirect flood footprint was 9.55 billion CNY. About 52% of this came from the tertiary industries, 40% from the secondary industries and the other 8% to the primary industries. Regarding the 42 sectors, construction, water conservation and transportation were found to account for the largest flood footprint, with shares over 12%, 10% and 9% respectively, of total area's flood footprint. These results seem to correspond closely with the industrial output composition of Beijing in 2012.

7.2. Contribution

This thesis comprehensively addresses the question of '***How to measure flood induced economic costs cascading throughout production supply chains***?' through a variety of calculations. As a new indicator that has been proposed in recent years, flood footprint is selected here to express flood footprint resulting from flood-related disasters on the affected region and the wider economic system, through both direct and indirect means. An effective framework for assessing flood footprint comprised of four steps (see Figure 1.2) is first recommended. Based on the idea of the flood footprint, this study offers many new insights into flood-induced economic impact assessment. The primary contributions of this research are summarised as follows:

1) **It has constructed a quantitative methodology framework of flood footprint analysis in accounting either single or multiple flood-induced economic costs cascading throughout production supply chains and estimated economic impacts at industrial and regional level in a certain time period with a clear modelling progression.**

Thanks to the Input-output theory and ARIO models in particular, the methodology framework of the Flood Footprint Model developed by this research is able to quantify the indirect economic effect of floods, by taking into consideration the interdependencies of the industrial and regional economy. Compared with the original model developed by Li et al. (2013) and other relevant Input-output models, certain factors, such as import and basic demand, are considered more rationally and accurately in the Flood Footprint Model through mathematical and logical approaches. Within a clear rationing scheme that is described in Chapter 3.2, the main achievements of the methodology are summarized as follows.

First, both industrial and household capital restrictions can be regarded as either exogenous or endogenous variables in the aftermath of a flood, according to different recovery plans. The existing ARIO models regard capital as an exogenous factor that is determined by external decisions. In this approach, if there is no specific recovery plan for damaged capital, its recovery is determined by the Flood Footprint Model in which the basic rationing scheme defines the recovered capital at each stage.

Second, the way that the impact of labour is assessed becomes more reliable by linking labour constraints with total production capacity. Few studies focus on flood-induced labour influence within an economy. Although the Post-disaster Imbalances Model (Steenge and Bočkarjova, 2007) suggests a way to take labour into consideration by introducing labour coefficients, it is unable to show how the affected labour influences the available production capacity. BDI model (Li et al., 2013) provides a means to illustrate the linkages between labour and productivity, but the direct labour influence on the economy is based on external assumptions. The Flood Footprint Model builds a bridge between labour affected and remaining production capacity via a variable named damage fraction of labour productivity. Meanwhile, the value of this variable used in the first period, in terms of the direct labour influence, can be calculated with practical data by converting labour time loss to degraded labour productivity.

Third, it provides a more effective rationing scheme of available resources in the aftermath of floods with consideration of basic human requirements. Current rationing schemes employed in the relevant models fall short of discussing basic human demand and just show rough directions of allocation without an exhaustive modelling process. The model presented in this research has established a reliable rationing scheme that is able to take account of basic human requirements in the post-flood period and present a comprehensive distributed process in which the various rationing scenarios are analysed.

Fourth, in the light of its different research goals and scope, the model is able to estimate the indirect flood footprint at industrial, regional or economic level within a specific time unit. **Fifth**, the flexibility of the model allows for various types of sensitivity analyses to model parameters and other external influences such as quality of post-flood governance in which recovery process can be clearly simulated. **Sixth**, this approach is able to quantify the indirect economic impact of both single-flood and two-flood disasters. In a multi-hazard disaster, the model can provide various thresholds of specific model parameters in order to draw up effective recovery plans in the future. **As a final point**, this methodology framework focuses on extending our insights into the role of capital and labour constraints, the contribution of imports to the reconstruction process, the behaviour of final consumers, and the consideration of 'basic demand', i.e. the minimum level of goods needed to satisfy the basic needs of the people concerned.

2) **Three illustrations of the approach improved by this research have been provided to demonstrate the flexibility and feasibility of the approach and explain the linkages between direct, indirect and total economic impact of a particular flood within a given economic system.**

Three case studies are used to test whether the Flood Footprint Model can be employed in both single and multiple flood cases. The results show that this model is more flexible in assessing the industrial and regional indirect flood footprint caused by individual or multiple floods. In particular, it is the first time that the Flood Footprint Model has been applied to a real case study at the regional level (Chapter 5). In addition, this study has also analysed the relationships between the flood footprints in selected cases. The most crucial link both at industrial and regional level, is between direct flood footprint and indirect flood footprint via inter-linkages among industries. Thus, in an economy, the industry that generates the highest direct flood footprint does not automatically generate the highest indirect flood footprint. The study has also shown that the total and indirect flood footprints of two-flood case are larger than the sum of the individual total and indirect flood footprints.

3) **The sensitivity of flood footprint to model parameters and other external factors has been analysed, and several options of post-flood economic recovery conditions outlined that are of benefit to policy- makers and stakeholders when making recovery-related decisions.**

Since real data for model validation is unavailable, sensitivity analyses on post-flood economic recovery makes a significant contribution to recovery design and flood risk management. The complexities real-life disasters require a more efficient approach to flood risk management than existing models provide. By using post-disaster economic recovery scenarios, the Flood Footprint Model is supports a variety of sensitivity analyses according to various recovery schemes. In the light of the flood footprint assessment, more informed decisions about post-flood economic recovery can be made and more effective plans drawn up by policy makers and stakeholders.

7.3. Policy Implications

It seems that rational decision-making tools can sometimes improve processes and outcomes of governance at the same time, so that risk management becomes central to the business of good government. Flood risk management and governance suggests that governance resources, including financial aid, regulatory and informational measures, should be rationed on the basis of risk calculations. This implies that more reliable economic impact measurements are of benefit to the construction of more efficient post-flood economic recovery plans (Krieger, 2013, Rothstein et al., 2006). However, it is seldom clear how indirect economic loss is distributed among sectors and the economy, and thus far, little has been known about post-flood recovery at both sectoral and economic level. The Flood Footprint Model established by this research is able to fill the above knowledge gaps by simulating dynamic recovery trends for specific sectors, taking into account the different influencing factors. Flood footprint assessment is proposed as an effective approach to the analysis of flood-induced economic risk and provides data support for post-flood recovery and management. This study offers many new insights and identifies key issues that policy makers charged with post-flood economic impact management need to consider.

One issue is mitigation of the flood-related economic risk. Empirical evidence shows that disaster management does not only include relief work, but also emergency response and mitigating the disaster risk in the first place. Most natural hazard mitigation is focused on the safety of employees and prevention of immediate damage more than on the long-term business continuity operations (Corey and Deitch, 2011). According to the sensitivity analysis based on the Flood Footprint Model, policy-makers can easily decide which scenario will lead to the smallest economic impact and which recovery path is more appropriate for the affected economic system. For example, in the 2012 Beijing flood discussed in Chapter 5, if the imports or external aids in the aftermath were less than the amount of imports before the flood, the regional economy would not have been able to recover due to the loss of production flow between industries. In the case of Chapter 4, the total and indirect economic footprint of a linear labour recovery was smaller than the other three non-linear trajectories. Thus, linear path of labour recovery scheme in the hypothetical single flood case can lead to less flood footprint. With the sensitivity analysis offered by the Flood Footprint Model, the economic risk a flood disaster carries can be reduced through different effective and efficient post-flood recovery plans.

One can also make recovery decisions through altering the rationing scheme. A Rationing Scheme refers to the allocation of available resources, and reflects how the policy-makers or relevant stakeholders prepare for post-disaster recovery. As concluded by Webb et al. (2002) and Corey and Deitch (2011), there is no significant link between the use of post-disaster aid and recovery outcomes in a specific natural disaster. This indicates that direct financial aid from related governments, institutions or NGOs is often deployed inefficiently. This thesis offers a clear and flexible framework within which to make rationing decisions, with the possibility of modifying and controlling the model factors in each recovery phase. Therefore, the rationing scheme can be adjusted to various specific requirements and external economic conditions.

Another issue pertains to financial responsibility. Aerts, (2014, p.474) formulate this as a policy question: '*Who should pay to make NYC (or any city) more resilient to future flood disasters*?' Within an economic system, the 'who' refers to the stakeholders at all levels, including small businesses, specific sectors and economies. Existing studies have focused more on the household than on industry. The Flood Footprint Model facilitates the identification of the critical sectors since it is able to measure the economic impact for each sector. On the basis of the industrial flood footprint, stakeholders will have a comprehensive picture of *when and where the economic losses will come from*, as well as *which sector should be recovered as a priority*. Moreover, policy makers or disaster-associated institutions can make more efficient resolutions on *how to allocate the available production resources* and *how to dominate the accessible financial aids or imports*.

7.4. Limitations and Future Work

Although this thesis is relatively comprehensive in its approach to flood-induced risk analysis, in terms of flood footprint assessment, many limitations and challenges remain. From the data perspective, due to the lack of accessible data and information on flood damage and post-flood economies, various assumptions have been made in the modelling process, like the statistical data regarding labour recovery time and household adaptive consumption behaviour. Nonetheless, though different assumptions will have different influences on the results, the data used in this model represent the best options in terms of reflecting real disaster situations.

Regarding the methodology, as mentioned in Chapter 3, the Flood Footprint Model established by this research is not able to consider market-based mechanisms. This means that pricing was not taking into account research. After a flood disaster, the price of some goods may increase due to the demand surge and this can also influence the regional economic system (Steenge and Serrano, 2012). However, this factor only plays a relatively small economic role and furthermore, with efficient government management, the prices of most commodities tend to be kept stable during and post disaster. Next, it is difficult to verify or validate the results from the Flood Footprint Model, since there is no statistical data about how sectors and economic systems recover after a disaster. Therefore, validation of the results can only be found by comparing them to analyses in related studies.

With respect to case studies, a number of possibilities may occur due to the complexity of reality. First of all, external investment is not taken into account during the recovery period. Investment is an important part of input data, but due to a lack of investment data for each sector after the disaster, this study does not consider external investment for economic recovery. Secondly, in the case of multiple floods, double accounting may exist in the measurement of labour and capital damage. This means that some specific labour and physical capital may sustain damage from both the first and subsequent flood, then resulting in double accounting of the damage fractions. Last but not least, it is difficult to separate critical/labour capital and ordinary capital/labour and thus, this thesis does not distinguish between them. The different types of capital/labour may affect the rationing scheme and indirect economic footprint. In the future, policymakers would need to know the regional economic base, such as types of commerce and types of employment (professional, skilled and unskilled) before disasters (Lindell and Prater, 2003). Such information is important as vulnerable economic subunits can be identified and recovery plans can then be developed before disaster strikes.

Overall, more specific information should be collected and more effort should be made in future research to understand the flood footprint model and improve the accuracy of its model results in order to develop better risk analysis assessment tools and management strategies. Thus, there is an urgent and obvious need for further development of flood footprint assessment; meanwhile, several topics and directions of relevant research can be explored in the future.

Data is fundamental both for flood footprint accounting and model validation. Although we know that more accurate and reliable data leads to higher quality of results and more efficient assessment of flood footprint, existing databases associated with natural disasters merely focus on the affect on the population and total economic loss. Few surveys collate the data needed for indirect economic impact accounting. Apart from the regional Input-output Table, other data that is used in the Flood Footprint Model can be divided into three types: firstly, damage-related data is used that includes industrial labour, amount of industrial and household capital loss, based on regional and industrial surveys; the second type is recovery-related data, such as industrial labour and capital recovery, amounts of available imports and adaptive consumption in the aftermath of floods; lastly the model uses data regarding basic human demand that comes from external decisions. However, in practical flood cases, only information on total population affected and total regional economic cost can be obtained; all the other data is unavailable and inaccessible information. Hence, data-related work for better flood footprint assessment in the next stage would need to address two issues: firstly, what type of data should be collected and secondly, what type of data can be used when accurate local data is not available or how to handle the lack of required data. What is more, the major challenge of which type of data can be used for the validation of flood-induced economic impacts still neds to be addressed.

Another practical issue is how to identify and separate the critical capital and labour at industrial level. In reality, there are mainly three post-economy economic flood situations: one is that among the labour affected, particular labour may contribute more to the outcomes in their sectors, and then in these related sectors, the productivities that are constrained by labour will be influenced more than the productivity in other sectors; secondly, in certain sectors, damaged capital and affected labour may together lead to more economic loss than their separate economic impact. For instance, in sector A, 10% economic loss is from damaged capital and the other 10% loss comes from affected labour, so the final impacts will range from 10% to 20%. However, due to lack of data, this thesis is based on the assumptions that 1) all the sectors sustain the same proportion of labour damage; and 2) the total impact on industrial productivity depends on the maximum impact of labour and capital limitations. This suggests that adaptations at certain junctures and probably the introduction of one or more additional parameters are needed that regulate this matching between capital and labour. This issue remains as a research gap in the relevant literature and approaches since it largely depends on actual information.

In addition, based on the ARIO model founded by Hallegatte (2008), the Flood Footprint Model can be improved by incorporating price parameters, making it suitable for market-based mechanisms. Finally, the Flood Footprint Model should be applied to more cases of actual individual flooding and multiple flood disasters in particular in the future, in order to examine the feasibility and flexibility of this approach. As a consequence, future work should focus on developing more detailed and effective guidelines for the assessment of flood footprint.

Appendices

Appendix A. Supplementary Tables of Chapter 5

Table A.1 Code and name of 42 sectors in Beijing.

Code	Sector Name	Code	Sector Name	Code	Sector Name
S1	Agriculture and forestry, animal husbandry and fishery	S15	Metal goods	S29	Wholesale and retail trade
S2	Coal mining and washing	S16	General equipment	S30	Transportation and warehousing, post
S3	Oil and gas exploitation	S17	Special equipment	S31	Accommodation and catering
S4	Metal minerals mining	S18	Transport equipment	S32	Information transmission, computer services and software
S5	Non-metal minerals and other mining	S19	Electrical machinery and equipment manufacturing	S33	Finance
S6	Food, drink and tobacco	S20	Communications equipment, computers and other electronic equipment	S34	Real estate
S7	Textiles	S21	Instruments and meters	S35	Leasing and business services
S8	Leather and feather products	S22	Other manufacturing products	S36	Scientific research and technical services
S9	Wood processing and furniture manufacturing	S23	Scrap and waste	S37	Water conservancy, environment and public facilities management
S10	Printing and paper stationery and sporting goods manufacturing	S24	Metal goods and equipment services	S38	Resident and other services

S11	Petroleum refining, coking ,nuclear fuel processing	S25	Electricity production and supply	S39	Educational services
S12	Chemical products	S26	Gas production and supply	S40	Health, social security and social welfare
S13	Non-metallic mineral products	S27	Water production and supply	S41	Culture, sports and entertainment
S14	Metal smelting and rolling processing	S28	Construction	S42	Public administration and other sectors

Table A.2 Flood footprints of 42 sectors in Beijing.

Code	Flood Footprint (Million CNY)			Code	Flood Footprint (Million CNY)			Code	Flood Footprint (Million CNY)		
	Direct	Indirect	Total		Direct	Indirect	Total		Direct	Indirect	Total
S1	1524	141	1665	S15	20	68	88	S29	20	580	600
S2	20	198	218	S16	20	119	139	S30	1500	462	1962
S3	20	255	275	S17	20	96	116	S31	20	167	187
S4	20	57	77	S18	20	500	520	S32	20	400	420
S5	20	43	63	S19	20	139	159	S33	1000	505	1505
S6	20	184	204	S20	20	408	428	S34	1000	267	1267
S7	20	19	39	S21	20	46	66	S35	20	312	332
S8	20	50	70	S22	20	21	41	S36	20	475	495
S9	20	23	43	S23	20	3	23	S37	2000	63	2063
S10	20	120	140	S24	20	16	36	S38	20	92	112
S11	20	219	239	S25	500	479	979	S39	20	149	169
S12	20	310	330	S26	500	81	581	S40	500	135	635
S13	20	96	116	S27	500	59	559	S41	1000	142	1142
S14	20	280	300	S28	1000	1590	88	S42	20	187	207

Here, industrial direct flood footprint equals to the industrial direct flood footprint.

Appendix B. List of Terminology Terms

Notes: all the terminology terms introduced here are principally referred to natural disasters and regional economy.

Adaptive capacity – the ability of a system to response to a disaster through adapting change and mitigating the influences.

Direct Flood Footprint – Economic impact and/or loss caused by direct consequences of flood events, and it refers to the short-term physical impacts on natural resources, people and tangible assets.

Flood – A natural phenomenon that overflows of water submerges dry land. In other words, it is a covering by water of land not normally covered by water.

Flood Footprint – A measure of the total economic impact (relative to the pre-disaster level) that is directly and indirectly caused by a flood event in the flooded region and the wider economic system.

Indirect Flood Footprint – Economic impact/loss resulted from flood-induced labour delay, capital loss, and disruption of economic activities in the whole production supply chain and costs for physical capital reconstruction.

Multi-hazard – 1) the selection of multiple major hazards that the country faces, and (2) the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects.

Multiple disasters - 1) the selection of multiple natural disasters that the region faces, and 2) the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects.

Natural catastrophe - A catastrophe is an extremely severe adverse shock, which causes a substantial disruption of the system, with well-specified spatial and temporal dimensions, to the extent that it fails to perform its vital functions for a considerable period of time, or forever.

Natural disaster – A discontinuity that resulted from interaction between a natural phenomenon and a human-induced system, where the system becomes adversely affected beyond the scale of minor changes, implying loss of connectivity within the established system, with wee-specified spatial and temporal dimensions.

Natural hazard – A natural processes and phenomena that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation.

Rapid-onset/sudden-onset natural disaster – A natural events that occur suddenly and strike rapidly with little warning.

Resilience of economy – The ability of an economy survive with the lowest damage and impact.

Slow-onset/persistent natural disaster – A natural hazards that take far longer, may be several months or years to develop, include disasters like heat wave, drought, desertification, air pollution, erosion, insect infestations, subsidence and disease epidemics

Vulnerability of economy – A system's exposure and sensitivity to a disaster-induced harm.

Regional threshold for damaged capital - The range of fractions on damaged capital resulted by floods that are suitable for regional adaptive resilience (only mentioned in Chapter 6).

References

ADGER, W. N., HUGHES, T. P., FOLKE, C., CARPENTER, S. R. & ROCKSTRÖM, J. 2005. Social-ecological resilience to coastal disasters. *Science,* 309**,** 1036-1039.

AERTS, J. C., BOTZEN, W. W., EMANUEL, K., LIN, N., DE MOEL, H. & MICHEL-KERJAN, E. O. 2014. Evaluating flood resilience strategies for coastal megacities. *Science,* 344**,** 473-475.

AHRENS, J. & RUDOLPH, P. M. 2006. The importance of governance in risk reduction and disaster management. *Journal of contingencies and crisis management,* 14**,** 207-220.

ALBALA-BERTRAND, J.-M. 1993. Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development,* 21**,** 1417-1434.

ALBALA-BERTRAND, J. M. 2013. *Disasters and the networked economy*, Routledge.

ALEXANDER, D. 1997. The study of natural disasters, 1977–97: some reflections on a changing field of knowledge. *Disasters,* 21**,** 284-304.

ALEXANDER, D. C. 2017. *Natural disasters*, Routledge.

ALFIERI, L., BISSELINK, B., DOTTORI, F., NAUMANN, G., ROO, A., SALAMON, P., WYSER, K. & FEYEN, L. 2017. Global projections of river flood risk in a warmer world. *Earth's Future,* 5**,** 171-182.

AMADEO, K. 2018. *Hurricane Katrina Facts, Damage, and Costs* [Online]. https://www.thebalance.com/hurricane-katrina-facts-damage-and-economic-effects-3306023. [Accessed 1 June 2018].

ANDERSON, C., SANTOS, J. & HAIMES, Y. Risk modeling, assessment, and management of the August 2003 northeast blackout. Society for Risk Analysis Annual Meeting, full report printed by the Center for Risk Management of Engineering Systems, University of Virginia, Charlottesville, VA, 2004.

AON BENFIELD 2015. Global Catastrophe Recap July 2015. *Aon Benfield Analytics/Impact Forecasting in July, 2015.*

AON BENFIELD 2017a. 2016 Annual global climate and catastrophe report. Impact Forecasting and Aon Benfield, Chicago, Illinois.

AON BENFIELD 2017b. Weather, Climate & Catastrophe Insight. Impact Forecasting and Aon Benfield, Chicago, Illinois.

ARNBJERG-NIELSEN, K. 2014. Climate change adaptation to increased urban flood risk: comparing the socio economic efficiency of water sensitive urban design practices with upgrading traditional infrastructure. *Technology,* 63**,** 527-535.

AROCHE REYES, F. & MARQUEZ MENDOZA, M. A. 2013. The demand driven and the supply-sided Input-Output models. Notes for the debate.

ASGARY, A., ANJUM, M. I. & AZIMI, N. 2012. Disaster recovery and business continuity after the 2010 flood in Pakistan: Case of small businesses. *International journal of disaster risk reduction,* 2**,** 46-56.

BAADE, R. A., BAUMANN, R. & MATHESON, V. 2007. Estimating the economic impact of natural and social disasters, with an application to Hurricane Katrina. *Urban Studies,* 44**,** 2061-2076.

BAGHERSAD, M. & ZOBEL, C. W. 2015. Economic impact of production bottlenecks caused by disasters impacting interdependent industry sectors. *International Journal of Production Economics,* 168**,** 71-80.

BAKER, J. L. 2012. *Climate change, disaster risk, and the urban poor: cities building resilience for a changing world*, World Bank Publications.

BANKOFF, G. 2001. Rendering the world unsafe:'vulnerability'as western discourse. *Disasters,* 25**,** 19-35.

BARRO, R. J. 1991. Economic growth in a cross section of countries. *The quarterly journal of economics,* 106**,** 407-443.

BBC. 2014. *Coastal flooding* [Online]. http://www.bbc.co.uk/schools/gcsebitesize/geography/coasts/coastal_flooding_rev1.shtml. [Accessed 1 June 2018].

BBC. 2015. *Floods and power loss after storm (5 Dec 2015)* [Online]. http://www.bbc.co.uk/news/live/uk-35015243: BBC NEWS. [Accessed 2 May 2018].

BELL, R. & GLADE, T. 2004. Multi-hazard analysis in natural risk assessments. *WIT Transactions on Ecology and the Environment,* 77.

BENSON, C. & TWIGG, J. 2004. Measuring mitigation: methodologies for assessing natural hazard risks and the net benefits of mitigation. Provention Consortium.

BERKE, P. R. & CAMPANELLA, T. J. 2006. Planning for postdisaster resiliency. *The Annals of the American Academy of Political and Social Science,* 604**,** 192-207.

BGS. 2017. *Groundwater Flooding* [Online]. https://www.bgs.ac.uk/research/groundwater/flooding/home.html: British Geological Survey. [Accessed 10th Oct. 2018].

BOCKARJOVA, M. 2007. *Major Disasters in Modern Economics.* PhD Thesis.

BOETTKE, P., CHAMLEE-WRIGHT, E., GORDON, P., IKEDA, S., LEESON, P. T. & SOBEL, R. 2007. The political, economic, and social aspects of Katrina. *Southern Economic Journal*, 363-376.

BROOKSHIRE, D. S., CHANG, S. E., COCHRANE, H., OLSON, R. A., ROSE, A. & STEENSON, J. 1997. Direct and indirect economic losses from earthquake damage. *Earthquake Spectra,* 13**,** 683-701.

BRUNEAU, M., CHANG, S. E., EGUCHI, R. T., LEE, G. C., O'ROURKE, T. D., REINHORN, A. M., SHINOZUKA, M., TIERNEY, K., WALLACE, W. A. & VON WINTERFELDT, D. 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake spectra,* 19**,** 733-752.

BURTON, C. G. 2015. A validation of metrics for community resilience to natural hazards and disasters using the recovery from Hurricane Katrina as a case study. *Annals of the Association of American Geographers,* 105**,** 67-86.

BURTON, I., HUQ, S., LIM, B., PILIFOSOVA, O. & SCHIPPER, E. L. 2002. From impacts assessment to adaptation priorities: the shaping of adaptation policy. *Climate policy,* 2**,** 145-159.

BURTON, I. & KATES, R. W. 1964. The perception of natural hazards in resource management. *Natural Resources Journal,* 3**,** 412-441.

CANTILLON, R. 1756. *Essai sur la nature du commerce*.

CARPIGNANO, A., GOLIA, E., DI MAURO, C., BOUCHON, S. & NORDVIK, J. P. 2009. A methodological approach for the definition of multi-risk maps at regional level: first application. *Journal of risk research,* 12**,** 513-534.

CARRERA, L., STANDARDI, G., BOSELLO, F. & MYSIAK, J. 2015. Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. *Environmental Modelling & Software,* 63**,** 109-122.

CASELLI, F. & MALHOTRA, P. 2004. Natural disasters and growth: from thought experiment to natural experiment. working paper, Harvard University.

CAVALLO, E., GALIANI, S., NOY, I. & PANTANO, J. 2013. Catastrophic natural disasters and economic growth. *Review of Economics and Statistics,* 95**,** 1549-1561.

CERRA, V. & SAXENA, S. C. 2008. Growth dynamics: the myth of economic recovery. *American Economic Review,* 98**,** 439-57.

CHARVÉRIAT, C. 2000. Natural disasters in Latin America and the Caribbean: An overview of risk.

CHEN, J., HILL, A. A. & URBANO, L. D. 2009. A GIS-based model for urban flood inundation. *Journal of Hydrology,* 373**,** 184-192.

CHEN, M., LIU, W. & TAO, X. 2013. Evolution and assessment on China's urbanization 1960–2010: under-urbanization or over-urbanization? *Habitat International,* 38**,** 25-33.

CHRISTOPLOS, I., MITCHELL, J. & LILJELUND, A. 2001. Re-framing risk: the changing context of disaster mitigation and preparedness. *Disasters,* 25**,** 185-198.

CLARK, C. 1967. The conditions of economic progress. *The conditions of economic progress.*

COCHRANE, H. 1997. Economic impacts of a Midwestern earthquake. NCEER Bulletin.

COCHRANE, H. C. 1974. Predicting the economic impact of earthquakes. *Social Science Perspectives on the Coming San Francisco Earthquake, Natural Hazards Research Paper,* 25.

COLE, S. 1995. Lifelines and livelihood: a social accounting matrix approach to calamity preparedness. *Journal of Contingencies and Crisis Management,* 3**,** 228-246.

COLE, S. 1998. Decision support for calamity preparedness: socioeconomic and interregional impacts. *Engineering and socioeconomic impacts of earthquakes***,** 125-153.

COLE, S., PANTOJA LOZANO, E. & RAZAK, V. 1993. Social accounting for disaster preparedness and recovery planning. *Technical report NCEER.* US National Center for Earthquake Engineering Research.

COREY, C. M. & DEITCH, E. A. 2011. Factors affecting business recovery immediately after Hurricane Katrina. *Journal of Contingencies and crisis management,* 19**,** 169-181.

CRED 2015a. The human cost of natural disasters 2015: a global perspective. Centre for Research on the Epidemiology of Disasters

CRED, U. 2015b. The human cost of weather related disasters (1995-2015). https://www.unisdr.org/we/inform/publications/46796: Centre for Research on the Epidemiology of Disasters, The United Nations Office for Disaster Risk Redution.

CRED, U. 2016. Poverty & Death: Disaster Mortality 1996-2015. Centre for Research on the Epidemiology of Disasters; The United Nations for Disaster Risk Reduction.

CROWTHER, K. G. & HAIMES, Y. Y. 2005. Application of the inoperability input—output model (IIM) for systemic risk assessment and management of interdependent infrastructures. *Systems Engineering,* 8**,** 323-341.

CUARESMA, C., JESÚS, HLOUSKOVA, J. & OBERSTEINER, M. 2008. Natural disasters as creative destruction? Evidence from developing countries. *Economic Inquiry,* 46**,** 214-226.

CUNADO, J. & FERREIRA, S. 2014. The macroeconomic impacts of natural disasters: the case of floods. *Land economics,* 90**,** 149-168.

CUTTER, S. L. 1996. Vulnerability to environmental hazards. *Progress in human geography,* 20**,** 529-539.

CUTTER, S. L., BARNES, L., BERRY, M., BURTON, C., EVANS, E., TATE, E. & WEBB, J. 2008. A place-based model for understanding community resilience to natural disasters. *Global environmental change,* 18**,** 598-606.

CUTTER, S. L. & FINCH, C. 2008. Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences,* 105**,** 2301-2306.

DABLA-NORRIS, E. & GÜNDÜZ, Y. B. 2014. Exogenous shocks and growth crises in low-income countries: A vulnerability index. *World Development,* 59**,** 360-378.

DARAMOLA, A. Y., ONI, O. T., OGUNDELE, O. & ADESANYA, A. 2016. Adaptive capacity and coping response strategies to natural disasters: a study in Nigeria. *International Journal of Disaster Risk Reduction,* 15**,** 132-147.

DE MOEL, H., VAN VLIET, M. & AERTS, J. C. 2014. Evaluating the effect of flood damage-reducing measures: a case study of the unembanked area of Rotterdam, the Netherlands. *Regional environmental change,* 14**,** 895-908.

DERANIYAGALA, S. 2016. *Economic Recovery after Natural Disasters* [Online]. UN Chronicle webpage. Available: https://unchronicle.un.org/article/economic-recovery-after-natural-disasters [Accessed May 1 2018].

DERYUGINA, T., KAWANO, L. & LEVITT, S. 2014. The economic impact of hurricane katrina on its victims: evidence from individual tax returns. National Bureau of Economic Research.

DESA 2016. *The World's Cities in 2016*, Department of Economic and Social Affairs, United Nations.

DFID 2012. Multi-hazard disaster risk assessment. *The DFID Business Plan for 2012-2015* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/204933/Multi-hazard_risk_assessment_guidance.pdf: Department for International Development 2012, Department for International Development,UK

DIETCH, E. A. & COREY, C. M. 2011. Predicting long-term business recovery four years after Hurricane Katrina. *Management Research Review,* 34**,** 311-324.

DIETZENBACHER, E. & MILLER, R. E. 2015. Reflections on the inoperability input–output model. *Economic Systems Research,* 27**,** 478-486.

DOOCY, S., DANIELS, A., MURRAY, S. & KIRSCH, T. D. 2013. The human impact of floods: a historical review of events 1980-2009 and systematic literature review. *PLoS currents,* 5.

EAKIN, H., BOJÓRQUEZ-TAPIA, L. A., JANSSEN, M. A., GEORGESCU, M., MANUEL-NAVARRETE, D., VIVONI, E. R., ESCALANTE, A. E., BAEZA-CASTRO, A., MAZARI-HIRIART, M. & LERNER, A. M. 2017. Opinion: Urban resilience efforts must consider social and political forces. *Proceedings of the National Academy of Sciences,* 114**,** 186-189.

ESPINOZA, S., PANTELI, M., MANCARELLA, P. & RUDNICK, H. 2016. Multi-phase assessment and adaptation of power systems resilience to natural hazards. *Electric Power Systems Research,* 136**,** 352-361.

EU 2007. DIRECTIVE 2007/60/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL OF 23 October 2007 on the assessment and management of flood risks. Brussels: Official Journal of the European Union: European Union.

FAROOQM, S. 2018. Floods: Occurrence and Distribution. http://www.geol-amu.org/notes/be1a-3-1.htm: Department of Geology, Aligarh Muslim University, India.

FIELD, C. B., BARROS, V., STOCKER, T. F. & DAHE, Q. 2012. *Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*, Cambridge University Press.

FISHER, A. G. 1939. Production, primary, secondary and tertiary. *Economic record,* 15**,** 24-38.

FLOODSITE 2009.

Flood risk assessment and flood risk management. An introduction and guidance bas ed on experiences and findings of FLOODsite (an EU-funded Integrated Project). Website of FLOODsite: Delft Hydraulics, Delft, the Netherlands

FOLKE, C. 2006. Resilience: The emergence of a perspective for social–ecological systems analyses. *Global environmental change,* 16**,** 253-267.

FOMBY, T., IKEDA, Y. & LOAYZA, N. V. 2013. The growth aftermath of natural disasters. *Journal of Applied Econometrics,* 28**,** 412-434.

GALLINA, V., TORRESAN, S., CRITTO, A., SPEROTTO, A., GLADE, T. & MARCOMINI, A. 2016. A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. *Journal of environmental management,* 168**,** 123-132.

GOV.UK. 2014. *Groundwater: current status and flood risk* [Online]. https://www.gov.uk/government/collections/groundwater-current-status-and-flood-risk: Environment Agency. [Accessed 10th Oct. 2018].

GREIVING, S. 2006. Integrated risk assessment of multi-hazards: a new methodology. *Special Paper-Geological Survey of Finland,* 42**,** 75.

GRIGG, N. S. & HELWEG, O. J. 1975. State-of-the-art of estimating flood damage in urban areas. *JAWRA Journal of the American Water Resources Association,* 11**,** 379-390.

HADDAD, E. A. & TEIXEIRA, E. 2015. Economic impacts of natural disasters in megacities: The case of floods in São Paulo, Brazil. *Habitat International,* 45**,** 106-113.

HAIMES, Y. Y. & JIANG, P. 2001. Leontief-based model of risk in complex interconnected infrastructures. *Journal of Infrastructure systems,* 7**,** 1-12.

HALLEGATTE, S. 2008. An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina. *Risk analysis,* 28**,** 779-799.

HALLEGATTE, S. 2014. Modeling the role of inventories and heterogeneity in the assessment of the economic costs of natural disasters. *Risk analysis,* 34**,** 152-167.

HALLEGATTE, S., GREEN, C., NICHOLLS, R. J. & CORFEE-MORLOT, J. 2013. Future flood losses in major coastal cities. *Nature climate change,* 3**,** 802.

HALLEGATTE, S., HOURCADE, J.-C. & DUMAS, P. 2007. Why economic dynamics matter in assessing climate change damages: illustration on extreme events. *Ecological economics,* 62**,** 330-340.

HALLEGATTE, S. & PRZYLUSKI, V. 2010. The economics of natural disasters: concepts and methods. *World Bank Policy Research Working Paper Series, Vol*.

HALLEGATTE, S., RANGER, N., MESTRE, O., DUMAS, P., CORFEE-MORLOT, J., HERWEIJER, C. & WOOD, R. M. 2011. Assessing climate change impacts, sea level rise and storm surge risk in port cities: a case study on Copenhagen. *Climatic Change,* 104**,** 113-137.

HAMMOND, M. J., CHEN, A. S., DJORDJEVIĆ, S., BUTLER, D. & MARK, O. 2015. Urban flood impact assessment: A state-of-the-art review. *Urban Water Journal,* 12**,** 14-29.

HEGER, M., JULCA, A. & PADDISON, O. 2008. *Analysing the impact of natural hazards in small economies: the Caribbean case*, Research Paper, UNU-WIDER, United Nations University (UNU).

HEWITT, K. & BURTON, I. 1971. *Hazardousness of a place: a regional ecology of damaging events*, Toronto Press, Toronto.

HOCHRAINER, S. 2009. Assessing the macroeconomic impacts of natural disasters: are there any?

HOEKSTRA, A. Y., CHAPAGAIN, A. K. & ALDAYA, M. M. 2011. *The water footprint assessment manual*.

HOEKSTRA, A. Y. & HUNG, P. Q. 2002. Virtual water trade: a quantification of virtual water flows between nations in relation to international crop trade. *Value of water research report series.* UNESCO-IHE, Delft, the Netherlands.

HOLLING, C. S. 1973. Resilience and stability of ecological systems. *Annual review of ecology and systematics,* 4**,** 1-23.

HORLICK-JONES, T. 1995. Modern disasters as outrage and betrayal. *International Journal of Mass Emergencies and Disasters,* 13**,** 305-315.

HUSBY, T. G., GROOT, H. L., HOFKES, M. W. & DRÖES, M. I. 2014. Do floods have permanent effects? Evidence from the Netherlands. *Journal of Regional Science,* 54**,** 355-377.

IKEUCHI, H., HIRABAYASHI, Y., YAMAZAKI, D., MUIS, S., WARD, P. J., WINSEMIUS, H. C., VERLAAN, M. & KANAE, S. 2017. Compound simulation of fluvial floods and storm surges in a global coupled river-coast flood model: Model development and its application to 2007 C yclone S idr in B angladesh. *Journal of Advances in Modeling Earth Systems,* 9**,** 1847-1862.

IN DEN BÄUMEN, H. S., TÖBBEN, J. & LENZEN, M. 2015. Labour forced impacts and production losses due to the 2013 flood in Germany. *Journal of hydrology,* 527**,** 142-150.

IPCC 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, New York, USA: Intergovernmental Panel on Climate Change.

IPCC 2014a. Annex II - Glossary. https://www.ipcc.ch/pdf/assessment-report/ar5/wg2/WGIIAR5-AnnexII_FINAL.pdf: Intergovernmental Panel on Climate Change, Cambridge University Press

IPCC 2014b. The Fifth Assessment Report: Climate Change 2014 Synthesis Report Summary for Policymakers http://ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_SPM.pdf: Intergovernmental Panel on Climate Change.

JOHNSON, K., DEPIETRI, Y. & BREIL, M. 2016. Multi-hazard risk assessment of two Hong Kong districts. *International Journal of Disaster Risk Reduction,* 19**,** 311-323.

JONGMAN, B., HOCHRAINER-STIGLER, S., FEYEN, L., AERTS, J. C., MECHLER, R., BOTZEN, W. W., BOUWER, L. M., PFLUG, G., ROJAS, R. & WARD, P. J. 2014. Increasing stress on disaster-risk finance due to large floods. *Nature Climate Change,* 4**,** 264.

JONKMAN, S. N., BOČKARJOVA, M., KOK, M. & BERNARDINI, P. 2008. Integrated hydrodynamic and economic modelling of flood damage in the Netherlands. *Ecological economics,* 66**,** 77-90.

KAPPES, M. S., KEILER, M., VON ELVERFELDT, K. & GLADE, T. 2012. Challenges of analyzing multi-hazard risk: a review. *Natural hazards,* 64**,** 1925-1958.

KELLENBERG, D. & MOBARAK, A. M. 2011. The economics of natural disasters. *Annu. Rev. Resour. Econ.,* 3**,** 297-312.

KING, S. 2017. *What's the difference between hurricanes, cyclones and typhoons?* [Online]. http://www.bbc.co.uk/newsround/24879162: BBC. [Accessed 1 May 2018].

KLEIN, R. J., NICHOLLS, R. J. & THOMALLA, F. 2003. Resilience to natural hazards: How useful is this concept? *Global Environmental Change Part B: Environmental Hazards,* 5**,** 35-45.

KOKS, E., DE MOEL, H. & KOOMEN, E. 2012. Comparing Extreme Rainfall and Large-Scale Flooding Induced Inundation Risk–Evidence from a Dutch Case-Study. *Studies on water management issues.* InTech.

KOKS, E. E., BOČKARJOVA, M., DE MOEL, H. & AERTS, J. C. J. H. 2015a. Integrated Direct and Indirect Flood Risk Modeling: Development and Sensitivity Analysis. *Risk Analysis,* 35**,** 882-900.

KOKS, E. E., CARRERA, L., JONKEREN, O., AERTS, J. C. J. H., HUSBY, T. G., THISSEN, M., STANDARDI, G. & MYSIAK, J. 2016. Regional disaster impact analysis: comparing input–output and computable general equilibrium models. *Nat. Hazards Earth Syst. Sci.,* 16**,** 1911-1924.

KOKS, E. E., JONGMAN, B., HUSBY, T. G. & BOTZEN, W. J. 2015b. Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *environmental science & policy,* 47**,** 42-52.

KOKS, E. E. & THISSEN, M. 2016. A multiregional impact assessment model for disaster analysis. *Economic Systems Research,* 28**,** 429-449.

KRIEGER, K. 2013. The limits and variety of risk-based governance: The case of flood management in Germany and England. *Regulation & Governance,* 7**,** 236-257.

KROLL, C. A., LANDIS, J. D., SHEN, Q. & STRYKER, S. 1991. Economic impacts of the Loma Prieta earthquake: A focus on small businesses. *University of California Transportation Center*.

KUBAL, C., HAASE, D., MEYER, V. & SCHEUER, S. 2009. Integrated urban flood risk assessment-adapting a multicriteria approach to a city. *Natural Hazards and Earth System Sciences,* 9**,** 1881.

KURZ, H. D. & SALVADORI, N. 2000. 'Classical'roots of input-output analysis: A short account of its long prehistory. *Economic Systems Research,* 12**,** 153-179.

KURZ, H. D. & SALVADORI, N. 2006. Input–output analysis from a wider perspective: a comparison of the early works of Leontief and Sraffa. *Economic Systems Research,* 18**,** 373-390.

LEONTIEF, W. 1928. Die Wirtschaftals Kreislauf. 60**,** 577-623.

LEONTIEF, W. 1936. Quantitative Input-Output Relations in the Economic System of the United States. *Review of Economics and Statistics,* 18**,** 105-125.

LEONTIEF, W. 1953. Domestic production and foreign trade; the American capital position re-examined. *Proceedings of the American philosophical Society,* 97**,** 332-349.

LEONTIEF, W. 1987. *Input-output analysis,* The New Palgrave. A Dictionary of Economics. London: Macmillan.

LEONTIEF, W. 1991. The economy as a circular flow. *Structural change and economic dynamics,* 2**,** 181-212.

LEROY, S. A. 2006. From natural hazard to environmental catastrophe: Past and present. *Quaternary International,* 158**,** 4-12.

LI, J., CRAWFORD BROWN, D., SYDDALL, M. & GUAN, D. 2013. Modeling Imbalanced Economic Recovery Following a Natural Disaster Using Input-Output Analysis. *Risk analysis,* 33**,** 1908-1923.

LINDELL, M. K. & PRATER, C. S. 2003. Assessing community impacts of natural disasters. *Natural Hazards Review,* 4**,** 176-185.

LIU, B., SIU, Y. L. & MITCHELL, G. 2016. Hazard interaction analysis for multi-hazard risk assessment: a systematic classification based on hazard-forming environment. *Natural Hazards and Earth System Sciences,* 16**,** 629.

LUTHER, L. Disaster debris removal after hurricane Katrina: status and associated issues. 2006. Congressional Research Service, Library of Congress.

MARZOCCHI, W., GARCIA-ARISTIZABAL, A., GASPARINI, P., MASTELLONE, M. L. & DI RUOCCO, A. 2012. Basic principles of multi-risk assessment: a case study in Italy. *Natural hazards,* 62**,** 551-573.

MASTERS, J. & HENSON, B. 2016. *Earth's 5th Costliest Non-U.S. Weather Disaster on Record: China's $22 Billion Flood* [Online]. https://www.wunderground.com/blog/JeffMasters/earths-5th-costliest-nonus-weather-disaster-on-record-chinas-22.html: The Weather Underground. [Accessed 1 May 2018].

MECHLER, R. 2004. *Natural disaster risk management and financing disaster losses in developing countries*, Verlag Versicherungswirtsch.

MECHLER, R. 2009. Disasters and economic welfare: can national savings help explain post-disaster changes in consumption?

MEEROW, S., NEWELL, J. P. & STULTS, M. 2016. Defining urban resilience: A review. *Landscape and urban planning,* 147**,** 38-49.

MENDOZA-TINOCO, D., GUAN, D., ZENG, Z., XIA, Y. & SERRANO, A. 2017. Flood footprint of the 2007 floods in the UK: The case of the Yorkshire and The Humber region. *Journal of Cleaner Production*.

MENS, M. J., KLIJN, F., DE BRUIJN, K. M. & VAN BEEK, E. 2011. The meaning of system robustness for flood risk management. *Environmental science & policy,* 14**,** 1121-1131.

MERZ, B., KREIBICH, H., THIEKEN, A. & SCHMIDTKE, R. 2004. Estimation uncertainty of direct monetary flood damage to buildings. *Natural Hazards and Earth System Science,* 4**,** 153-163.

MIAN, S. 2014. Pakistan's Flood Challenges: An assessment through the lens of learning and adaptive governance. *Environmental Policy and Governance,* 24**,** 423-438.

MILLER, R. E. & BLAIR, P. D. 2009. *Input-output analysis: foundations and extensions*, Cambridge University Press.

MOFTAKHARI, H. R., SALVADORI, G., AGHAKOUCHAK, A., SANDERS, B. F. & MATTHEW, R. A. 2017. Compounding effects of sea level rise and fluvial flooding. *Proceedings of the National Academy of Sciences,* 114**,** 9785-9790.

MOLINARI, D., MENONI, S., ARONICA, G., BALLIO, F., BERNI, N., PANDOLFO, C., STELLUTI, M. & MINUCCI, G. 2014. Ex post damage assessment: an Italian experience. *Natural Hazards and Earth System Science,* 14**,** 901-916.

MORROW, B. H. 1999. Identifying and mapping community vulnerability. *Disasters,* 23**,** 1-18.

MORSINK, K. 2018. *Hurricanes, Typhoons, and Cyclones* [Online]. http://ocean.si.edu/hurricanes-typhoons-and-cyclones: Smithsonian National Museum of Natural History. [Accessed 1 May 2018].

MURLIDHARAN, T. & SHAH, H. 2003. *Economic consequences of catastrophes triggered by natural hazards.* Stanford University.

NASA. 2018. *A blanket around the Earth* [Online]. https://climate.nasa.gov/causes/: National Aeronautics and Space Administration. [Accessed 2 May 2018].

NATIONAL RESEARCH COUNCIL 1999. *The Impacts of Natural Disaster: A Framework for Loss Estimation,* Washington D.C., US, National Academies Press.

NATIONS, U. 2010. *Natural hazards, unnatural disasters: the economics of effective prevention*, The World Bank.

NELSON, S. A. 2014. Natural disasters & assessing hazards and risk. *Research Paper for Tulane University,* 20.

NORDHAUS, W. D. 2010. The economics of hurricanes and implications of global warming. *Climate Change Economics,* 1**,** 1-20.

NOS. 2018. *What is the difference between a hurricane and a typhoon?* [Online]. https://oceanservice.noaa.gov/facts/cyclone.html: National Ocean Service, National Oceanic and Atmospheric Administration, U.S. Department of Commerce. [Accessed 1 May 2018].

NOY, I. 2009. The macroeconomic consequences of disasters. *Journal of Development economics,* 88**,** 221-231.

NOY, I. & DUPONT IV, W. 2016. The long-term consequences of natural disasters—A summary of the literature.

NOY, I. & IV, W. D. 2016. The long-term consequences of natural disasters — A summary of the literature http://researcharchive.vuw.ac.nz/handle/10063/4981: School of Economics and Finance, Victoria Business School

NOY, I. & VU, T. B. 2010. The economics of natural disasters in a developing country: The case of Vietnam. *Journal of Asian Economics,* 21**,** 345-354.

NRC 1999. *The impacts of natural disasters: A framework for loss estimation*, National Research Council. National Academies Press.

NRC 2011. *Advancing the science of climate change*, National Research Council. National Academies Press.

O'KEEFE, P., WESTGATE, K. & WISNER, B. 1976. Taking the naturalness out of natural disasters. *Nature,* 260**,** 566-567.

OAS 1990. Disaster, planning and development: managing natural hazards to reduce loss.: Organization of American States, Department of Regional Development and Environment Executive Secretariat for Economic and Social Affairs Organization of American States, Washington, D.C.

OKUYAMA, Y. 2007. Economic modeling for disaster impact analysis: past, present, and future. *Economic Systems Research,* 19**,** 115-124.

OKUYAMA, Y. 2008. Critical review of methodologies on disaster impact estimation. *Background Paper to the Joint World Bank, UN Assessment on the Economics of Disaster Risk Reduction*.

OKUYAMA, Y. 2014. Disaster and economic structural change: case study on the 1995 Kobe earthquake. *Economic Systems Research,* 26**,** 98-117.

OKUYAMA, Y. & SAHIN, S. 2009. Impact estimation of disasters: a global aggregate for 1960 to 2007.

OKUYAMA, Y. & SANTOS, J. R. 2014. Disaster impact and input–output analysis. *Economic Systems Research,* 26**,** 1-12.

OOSTERHAVEN, J. 1988. On the plausibility of the supply-driven input-output model. *Journal of Regional Science,* 28**,** 203-217.

ORESKES, N. 2004. The scientific consensus on climate change. *Science,* 306**,** 1686-1686.

OTERO, R. C. & MARTI, R. Z. The impacts of natural disasters on developing economies: implications for the international development and disaster community. 1994. World Conference on Natural Disaster Reduction.

PALMER, L. 2013. Providing aid before climate disasters strike. Nature Publishing Group.

PARKER, D. J. 2014. *Floods*, Routledge.

PATHAK, S. & AHMAD, M. M. 2016. Flood recovery capacities of the manufacturing SMEs from floods: A case study in Pathumthani province, Thailand. *International Journal of Disaster Risk Reduction,* 18**,** 197-205.

PENNING-ROWSELL, E. & FORDHAM, M. 1994. *Floods across Europe: hazard assessment, modelling and management*, Middlesex University Press.

PENNING-ROWSELL, E., PRIEST, S., PARKER, D., MORRIS, J., TUNSTALL, S., VIAVATTENE, C., CHATTERTON, J. & OWEN, D. 2014. *Flood and coastal erosion risk management: a manual for economic appraisal*, Routledge.

PENNING-ROWSELL, E. C. & CHATTERTON, J. B. 1977. *The benefits of flood alleviation: A manual of assessment techniques*, Gower Technical Press, Aldershot.

PINGALI, P., ALINOVI, L. & SUTTON, J. 2005. Food security in complex emergencies: enhancing food system resilience. *Disasters,* 29**,** S5-S24.

POONTIRAKUL, P., BROWN, C., NOY, I., SEVILLE, E. & VARGO, J. 2016. The role of commercial insurance in post-disaster recovery: Quantitative evidence from the 2011 Christchurch earthquake.

PYATT, G. & ROUND, J. I. 1979. Accounting and fixed price multipliers in a social accounting matrix framework. *The Economic Journal,* 89**,** 850-873.

QUARANTELLI, E. L. 2001. Statistical and conceptual problems in the study of disasters. *Disaster Prevention and Management: An International Journal,* 10**,** 325-338.

RADDATZ, C. 2007. Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics,* 84**,** 155-187.

RASMUSSEN, M. T. N. 2004. *Macroeconomic implications of natural disasters in the Caribbean*, International Monetary Fund.

REES, W. E. 1992. Ecological footprints and appropriated carrying capacity: what urban economics leaves out. *Environment and urbanization,* 4**,** 121-130.

REMO, J. W., PINTER, N. & MAHGOUB, M. 2016. Assessing Illinois's flood vulnerability using Hazus-MH. *Natural Hazards,* 81**,** 265-287.

ROSE, A. 1995. Input-output economics and computable general equilibrium models. *Structural change and economic dynamics,* 6**,** 295-304.

ROSE, A., BENAVIDES, J., CHANG, S. E., SZCZESNIAK, P. & LIM, D. 1997. The regional economic impact of an earthquake: Direct and indirect effects of electricity lifeline disruptions. *Journal of Regional Science,* 37**,** 437-458.

ROSE, A. & GUHA, G.-S. 2004. Computable general equilibrium modeling of electric utility lifeline losses from earthquakes. *Modeling spatial and economic impacts of disasters.* Springer.

ROSE, A. & LIAO, S. Y. 2005. Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of Regional Science,* 45**,** 75-112.

ROSE, A. & LIM, D. 2002. Business interruption losses from natural hazards: conceptual and methodological issues in the case of the Northridge earthquake. *Global Environmental Change Part B: Environmental Hazards,* 4**,** 1-14.

ROTHSTEIN, H., IRVING, P., WALDEN, T. & YEARSLEY, R. 2006. The risks of risk-based regulation: Insights from the environmental policy domain. *Environment international,* 32**,** 1056-1065.

RUNYAN, R. C. 2006. Small business in the face of crisis: Identifying barriers to recovery from a natural disaster. *Journal of Contingencies and crisis management,* 14**,** 12-26.

SANTOS, J. R. 2006. Inoperability input-output modeling of disruptions to interdependent economic systems. *Systems Engineering,* 9**,** 20-34.

SANTOS, J. R. & HAIMES, Y. Y. 2004a. Modeling the Demand Reduction Input-Output (I-O) Inoperability due to Terrorism of Interconnected Infrastructures. *Risk Analysis,* 24**,** 1437-1451.

SCAWTHORN, C., BLAIS, N., SELIGSON, H., TATE, E., MIFFLIN, E., THOMAS, W., MURPHY, J. & JONES, C. 2006a. HAZUS-MH flood loss estimation methodology. I: Overview and flood hazard characterization. *Natural Hazards Review,* 7**,** 60-71.

SCAWTHORN, C., FLORES, P., BLAIS, N., SELIGSON, H., TATE, E., CHANG, S., MIFFLIN, E., THOMAS, W., MURPHY, J. & JONES, C. 2006b. HAZUS-MH flood loss estimation methodology. II. Damage and loss assessment. *Natural Hazards Review,* 7**,** 72-81.

SCHAFFER, W. A. 1999. *Regional impact models*, Regional Research Institute, West Virginia University.

SCHIPPER, L. & PELLING, M. 2006. Disaster risk, climate change and international development: scope for, and challenges to, integration. *Disasters,* 30**,** 19-38.

SF. 2018. *What is groundwater flooding?* [Online]. https://stormguardfloodplan.com/what-is-groundwater-flooding/: Stormguard Floodplan. [Accessed 10th Oct. 2018].

SHEPHERD, A., MITCHELL, T., LEWIS, K., LENHARDT, A., JONES, L., SCOTT, L. & MUIR-WOOD, R. 2013. The geography of poverty, disasters and climate extremes in 2030. https://www.odi.org/publications/7491-geography-poverty-disasters-climate-change-2030: The Overseas Development Institute

SHOVEN, J. B. & WHALLEY, J. 1992. *Applying general equilibrium*, Cambridge university press.

SIAGIAN, T. H., PURHADI, P., SUHARTONO, S. & RITONGA, H. 2014. Social vulnerability to natural hazards in Indonesia: driving factors and policy implications. *Natural hazards,* 70**,** 1603-1617.

SINANEWS. 2017. *Tropical Strom Pakhar lead to 3.1 billion CNY direct economic loss within 3 proviences in China (in Chinese)* [Online]. http://news.sina.com.cn/o/2017-08-29/doc-ifykiqfe2598347.shtml. [Accessed 1 June 2018].

SMITH, D. I. 1994. Flood damage estimation- A review of urban stage-damage curves and loss functions. *Water S. A.,* 20**,** 231-238.

SMITH, K. 2003. *Environmental hazards: assessing risk and reducing disaster*, Routledge.

SOLOW, R. M. 1956. A contribution to the theory of economic growth. *The quarterly journal of economics,* 70**,** 65-94.

SSA 2018. Storm Science. https://www.ausstormscience.com/storm-science/: Storm Science Australia.

STEENGE, A. E. & BOČKARJOVA, M. 2007. Thinking about imbalances in post-catastrophe economies: an input–output based proposition. *Economic Systems Research,* 19**,** 205-223.

STEENGE, A. E. & SERRANO, M. 2012. Income Distributions In Input-Output Models. *Economic Systems Research,* 24**,** 391-412.

STEVENSON, J., CHANG-RICHARDS, Y., CONRADSON, D., WILKINSON, S., VARGO, J., SEVILLE, E. & BRUNSDON, D. 2014. Organizational networks and recovery following the Canterbury earthquakes. *Earthquake Spectra,* 30**,** 555-575.

STONE, R. & BROWN, A. 1962. A computable model for economic growth. Cambridge, UK: Cambridge Growth Project.

STRÖMBERG, D. 2007. Natural disasters, economic development, and humanitarian aid. *Journal of Economic perspectives,* 21**,** 199-222.

SYDNOR, S., NIEHM, L., LEE, Y., MARSHALL, M. & SCHRANK, H. 2017. Analysis of post-disaster damage and disruptive impacts on the operating status of small businesses after Hurricane Katrina. *Natural Hazards,* 85**,** 1637-1663.

SZÖNYI, M., MAY, P. & LAMB, R. 2016. Flooding after Storm Desmond. http://www.jbatrust.org/wp-content/uploads/2016/08/flooding-after-storm-desmond-PUBLISHED-24-August-2016.pdf: JBA Trust, Zurich Insurance Group, JBA Consulting.

TIERNEY, K. J. 1995. Impacts of recent US disasters on businesses: the 1993 midwest floods and the 1994 Northridge Earthquake.

TIERNEY, K. J. 2007. Businesses and disasters: vulnerability, impacts, and recovery. *Handbook of disaster research.* Springer.

TURNER, B. A. 1976. The development of disasters—a sequence model for the analysis of the origins of disasters. *The Sociological Review,* 24**,** 753-774.

TWIGG, J. 2004. Disaster risk reduction: mitigation and preparedness in development and emergency programming. Overseas Development Institute (ODI).

UN-HABITAT 2016. *World cities report 2016. Urbanization and development. Emerging futures*, United Nations Human Settlements Programme

UN 2002. Johannesburg plan of Implementation of the World Summit on Sustainable Development. Tech. Rep. http://www.un.org/esa/sustdev/documents/WSSD_POI_PD/English/WSSD_Plan Impl.pdf: United Nations.

UNEP. Agenda 21. Tech. rep. United Nations Conferences on Environment & Development 1992 Rio de Janerio, Brzail. https://sustainabledevelopment.un.org/content/documents/Agenda21.pdf: United Nations Environment Programme.

UNGA 2016. Report of the open-ended intergovernmental expert working group on indicators and terminology relateing to disaster risk reduction *UN General Assembly Resolution A/71/644.* New York, NY.

UNISDR. 2017. *Terminology on disaster risk reduction* [Online]. https://www.unisdr.org/we/inform/terminology#letter-n: United Nations Office for Disaster Risk Reduction. [Accessed 26 April 2018].

VICKERY, P., SKERLJ, P. & TWISDALE, L. 2000a. Simulation of hurricane risk in the US using empirical track model. *Journal of structural engineering,* 126**,** 1222-1237.

VICKERY, P. J., LIN, J., SKERLJ, P. F., TWISDALE JR, L. A. & HUANG, K. 2006a. HAZUS-MH hurricane model methodology. I: Hurricane hazard, terrain, and wind load modeling. *Natural Hazards Review,* 7**,** 82-93.

VICKERY, P. J., SKERLJ, P., STECKLEY, A. & TWISDALE, L. 2000b. Hurricane wind field model for use in hurricane simulations. *Journal of Structural Engineering,* 126**,** 1203-1221.

VICKERY, P. J., SKERLJ, P. F., LIN, J., TWISDALE JR, L. A., YOUNG, M. A. & LAVELLE, F. M. 2006b. HAZUS-MH hurricane model methodology. II: Damage and loss estimation. *Natural Hazards Review,* 7**,** 94-103.

VISSER, H., PETERSEN, A. C. & LIGTVOET, W. 2014. On the relation between weather-related disaster impacts, vulnerability and climate change. *Climatic Change,* 125**,** 461-477.

VON NEUMANN, J. 1971. A model of general economic equilibrium. *Readings in the Theory of Growth.* Springer.

VON PETER, G., VON DAHLEN, S. & SAXENA, S. C. 2012. Unmitigated disasters? New evidence on the macroeconomic cost of natural catastrophes.

WAHL, T., JAIN, S., BENDER, J., MEYERS, S. D. & LUTHER, M. E. 2015. Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature Climate Change,* 5**,** 1093.

WALRAS, L. 2013. *Elements of pure economics*, Routledge.

WEBB, G. R., TIERNEY, K. J. & DAHLHAMER, J. M. 2002. Predicting long-term business recovery from disaster: a comparison of the Loma Prieta earthquake and Hurricane Andrew1. *Global Environmental Change Part B: Environmental Hazards,* 4**,** 45-58.

WHITE, G. F. 1974. *Natural hazards, local, national, global*, Oxford University Press.

WIEDMANN, T. & MINX, J. 2008. A definition of 'carbon footprint'. *Ecological economics research trends,* 1**,** 1-11.

WIKIPEDIA. 2005. *Hurricane Katrina* [Online]. https://en.wikipedia.org/wiki/Hurricane_Katrina. [Accessed 1 June 2018].

WIKIPEDIA. 2016. *2015–16 Great Britain and Ireland floods* [Online]. https://en.wikipedia.org/wiki/2015–16_Great_Britain_and_Ireland_floods: WIKIPEDIA. [Accessed 2 May 2018].

WIKIPEDIA. 2017a. *Hurricane Harvey* [Online]. https://en.wikipedia.org/wiki/Hurricane_Harvey. [Accessed 1 June 2018].

WIKIPEDIA. 2017b. *Hurricane Irma* [Online]. https://en.wikipedia.org/wiki/Hurricane_Irma. [Accessed 1 June 2018].

WIKIPEDIA. 2017c. *Hurricane Maria* [Online]. https://en.wikipedia.org/wiki/Hurricane_Maria. [Accessed 1 June 2018].

WIKIPEDIA. 2017d. *Tropical Storm Pakhar (2017)* [Online]. https://en.wikipedia.org/wiki/Tropical_Storm_Pakhar_(2017). [Accessed 1 June 2018].

WINSEMIUS, H. C., AERTS, J. C., VAN BEEK, L. P., BIERKENS, M. F., BOUWMAN, A., JONGMAN, B., KWADIJK, J. C., LIGTVOET, W., LUCAS, P. L. & VAN VUUREN, D. P. 2016. Global drivers of future river flood risk. *Nature Climate Change,* 6**,** 381.

WORKSHOP, D. 2017. *"Slow & rapid onset disasters"* [Online]. http://www.dwf.org/en/content/slow-rapid-onset-disasters Available: http://www.dwf.org/en/content/slow-rapid-onset-disasters [Accessed].

WRIGHT, L. A., KEMP, S. & WILLIAMS, I. 2011. 'Carbon footprinting': towards a universally accepted definition. *Carbon management,* 2**,** 61-72.

ZHAI, A. R. & JIANG, J. H. 2014. Dependence of US hurricane economic loss on maximum wind speed and storm size. *Environmental Research Letters,* 9**,** 064019.