# Innovations towards Climate-Induced Disaster Risk Assessment and Response

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**Abstract**

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A changing climate may portend increasing disaster risk across many countries and business enterprises. While many aspects of the hazards, exposure and vulnerability that constitute disaster risk have been well studied, several challenges remain. A critical aspect that needs to be addressed is the rapid response and recovery from a climate-induced disaster. Often, governments need to allocate funds or design financial instruments that can be activated rapidly to mobilize response and recovery. The proposed research addresses this general problem, focusing on a few selected issues. First, there is the question of how to rapidly detect and index a climate hazard, such as a flood, given proxy remote sensing data on attributes that may be closely related to the hazard. The second is the need to robustly estimate the return periods of extreme climate hazards, and the temporal changes in their projected frequency of occurrence using multi-century climate proxies. The third is the need to assess the potential losses from the event, including the disruption of services, and cascading failure of interlinked infrastructure elements. The fourth is the impact on global and regional supply chains that are induced by the event, and the associated financial impact. For each of these cases, it is useful to ground an analysis and the development of an approach around real world examples, which can then collectively inform a strategy for emergency response. Here, this will be pursued through an analysis of flooding in the Philippines, livestock mortality induced by drought and freezing winter in Mongolia, Hurricane Sandy impacts in New York, supply chain impacts in Thailand, and an end to end analysis of the potential process using data from Thailand and Bangladesh. Collectively, these analyses are expected to inform climate hazard planning and securitization processes with broad applicability at a regional to national level.

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# CHAPTER 1 INTRODUCTION

## 1.1 Introduction

As climate changes, hazards such as the frequency, intensity, spatial range, duration, and timing of extreme weather and climate events are also expected to change over time (IPCC, 2012). Disaster risks consist of hazards, exposure, and vulnerability. Traditionally, policymakers and researchers have focused on hazards for disaster risk management; however, it has become clear that they must regard exposure and vulnerability as key determinants of disaster risk and impacts when risk is realized (IPCC, 2012). If exposure and vulnerability will change over time, disaster risks will change as well. For example, unplanned urban development near coastal areas increases exposure. Furthermore, due to recent technological developments and economic globalization, societies are more interconnected at every level from international to regional scales. Therefore, because societies are more interdependent, disaster risks easily propagate to distant places, leading to increased vulnerability. The Economist (2012) reported a decrease in death rates from natural disasters over the course of 100 years. However, economic burden increased drastically. Connections among some determinants of risk and vulnerability, such as rapid urbanization, are clear. However, current knowledge does not quantify regional or global significances of these connections (IPCC, 2012). This research will explore how to improve financing for rapid recovery after catastrophic floods in terms of the analysis of hazards, exposure and vulnerability, taking selected issues at regional and national scales.

## 1.1 Motivation and Background

*Economic Losses are Increasing*

Economic losses at the global scale are increasing over more than 30 years. Economic losses caused by disaster amounted to US $ 3,800 billion worldwide (Figure 1-1). The line shows the increasing trend worldwide. Furthermore, some 87% of 18,200 reported disasters, 74% of US$ 2800 billion of losses, and 61% of 1.4 million of lost lives were attributed to weather and climate related extremes (World Bank 2013).

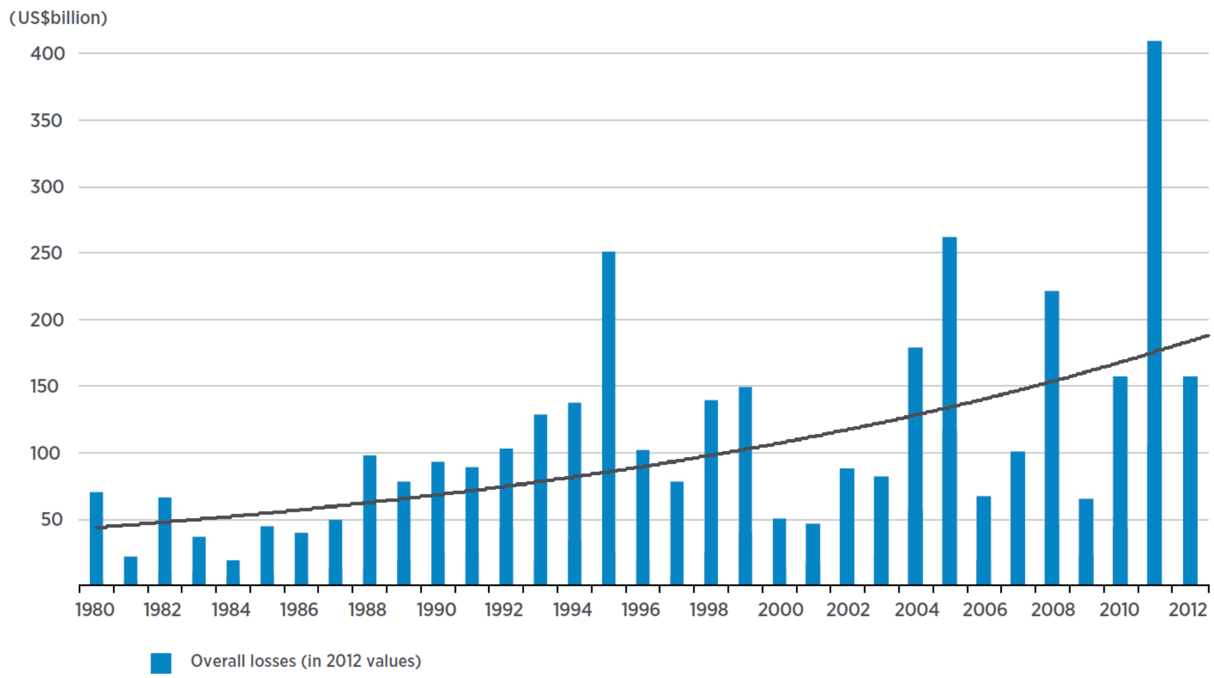


Figure 1-1: Global disaster losses from 1980 - 2012. The bars indicate annual disaster losses. The line indicates the trend. Adapted from World Bank (2013)

IPCC (2012) has high confidence that economic losses caused by weather-and climate-related disasters have increased with large spatial and interannual variability. Furthermore, IPCC (2012) estimates with high confidence that increasing exposure of people and economic assets has been the primary cause of long-term increases in economic losses from weather and climate related disasters. Thus, disaster risk and its components – hazards, exposure, and vulnerability – will be reviewed first.

## *Definition of Disaster Risk*

In this study, disasters are adverse impacts that "produce widespread damage and cause severe alterations in the normal functioning of communities or societies" (IPCC, 2012). Disaster risks can be defined as the function of hazards, exposure, and vulnerability (World Bank, 2013). A hazard is defined as "the potential occurrence of a natural or human-induced physical event that may cause loss of life, injury or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision and environmental resources" (IPCC 2007; IPCC 2012; the World Bank 2013). Exposure is defined as "The presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected." (IPCC, 2012; the World Bank 2013). Vulnerability is defined as "the propensity or predisposition to be adversely affected" (IPCC 2012).

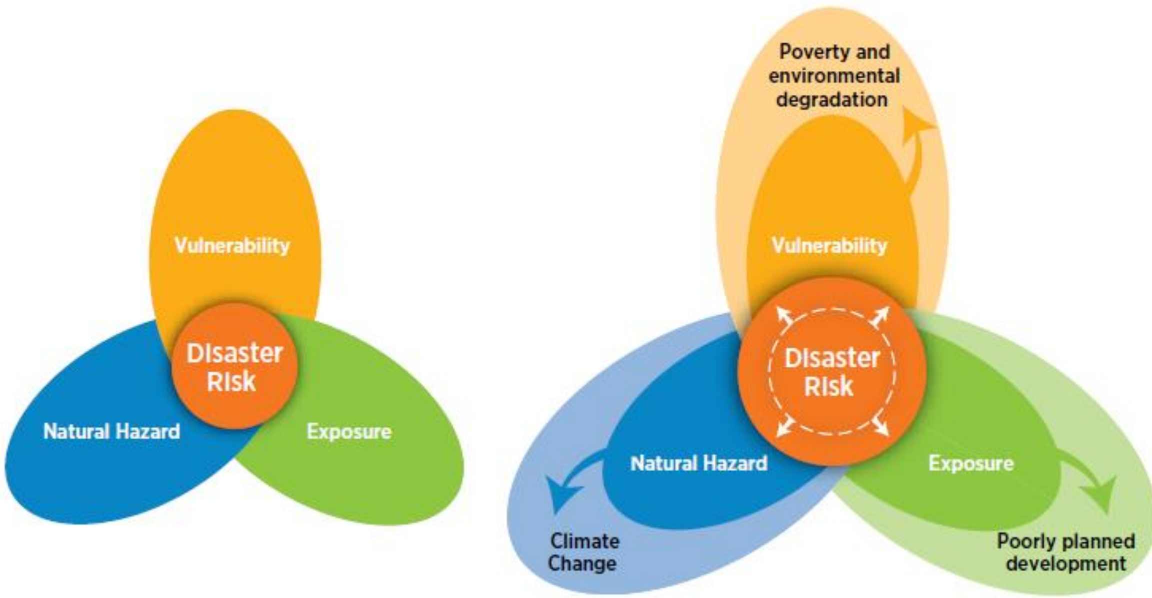


Figure 1-2: Conceptual idea of disaster risk. The right image shows that disaster risk will increase if any components – hazard, exposure, and vulnerability – increase. Adapted from World Bank (2013).

This study will adopt the definition of "holistic perspectives on vulnerability" (IPCC 2012), which distinguish exposure, susceptibility, and societal response capabilities as factors of vulnerability (Birkmann 2006; Cardona 1999; Carreño et al 2007; Cardona 2011). Societal response capabilities can be considered as adaptive capacity, which is defined in the climate adaptation field as the ability of a system to adjust to climate change in order to moderate potential damages, take advantage of opportunities, or cope with the consequences (IPCC 2007; IPCC 2012). Resilience is used in this study as the ability of a system and its component parts to anticipate, absorb, accommodate or recover from the effects of a hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration or improvement of its essential basic structures and functions (IPCC 2012).

### *Hazards, Exposure, and Vulnerability Are Changing*

Data since 1950 shows evidences of changes in some climate and weather extremes (IPCC 2012). Confidence in changes in extremes depends on the quality and quantity of data, which makes it challenging to identify long-term changes in extremes (IPCC, 2012). However, there are some significant changes observed in some regions.

It is critical to pay attention to the temporal and spatial dynamics of exposure and vulnerability as it is highly likely that trends in exposure and vulnerability are primary drivers of changes in disaster risk (IPCC 2012). IPCC (2012) claims that exposure and vulnerability differ across temporal and spatial scales, and depend on socio-economic, demographic, institutional, and environmental factors. Particularly, settlement patterns, urbanization, and changes in socioeconomic conditions have already affected observed trends in exposure and vulnerability to extreme weather and climate events (IPCC, 2012). Uitto (1998) argues that the development of megacities with high population density, such as Shanghai and Bangkok, has increased the exposure of people to disaster risks because of rapid unplanned development. Particularly, vulnerability is intertwined in a complex way with other socioeconomic factors, such as degree of interconnectedness of economy (Adger et al 2009; Gassebner et al 2010; Linnerooth-Bayer et al 2010; Kleindorfer 2009), degree of development, adaptive capacity and the degree of resilience in different levels of society (Haraguchi et al 2016).

In terms of the interconnectedness of society, due to the advancements in information technologies and globalization, societies and critical infrastructure systems are getting more and more interconnected. For example, the more interconnected global value chains are, the more likely economic losses are to increase (Haraguchi et al 2015). One point of failure in the supply chain leads to cascading failure of the entire system (Merz et al, 2014). For example, during the 2011 Japanese earthquake and Thailand floods, many factories which are located in a distant place from the affected regions had to reduce operations because of the stagnant sales and supply of parts. In addition, the more interconnected critical infrastructure is, the more economic damages and losses would occur. Failures of one sector will lead to failures in other sectors. A notable example is New York City during Hurricane Sandy. The blackout in the electric grids caused inoperability of other critical infrastructure such as waste water treatment systems, hospitals, and building operations.

## *Floods as Disaster Risks*

Economic losses caused by floods exceeded 19 billion USD in 2012 (Munich Re, 2013a; Ward et al, 2013) and have increased over the past 50 years (IPCC 2012; UNISDR 2011; Ward et al 2013). For flooding, existing studies (Merz et al 2014; Bubeck et at 2012) recognize the importance of analyzing changes in all three disaster risk components (hazards, exposure, and vulnerability) and of better understanding the interactions between society and floods. The vulnerability of a society to floods is dynamic and may change even during one single flood event (Kuhlicke et al, 2011).

In general, disaster risk components – hazards, exposure, and vulnerability – are spatially and temporally interdependent (Di Baldassarre 2013; Merz et al 2014). Extreme and non-extreme weather or climate events affect resilience, coping capacity and adaptive capacity, which eventually affect vulnerability to future extreme events (IPCC 2012). Measures designed to reduce hazards can lead to increased exposure of human beings. For example, flood protection measures, such as dikes, that reduce the flood hazard might promote urban development behind dikes and lower risk perceptions near the dikes, which leads to increasing exposure and vulnerability: the so-called levee effect (Tobin, 1995; Merz et al 2014). These spatial and temporal interdependencies must be addressed.

## *Overview*

Based on the framework of disaster risks, the following studies are proposed (Figure 1-3):

(1) Hazard: robustly identify floods in Manila, Philippines. The study will investigate how to detect flooding events in Metro Manila utilizing remote-sensing environmental data.

(2) Hazard: conduct risk analysis for dzud in Mongolia. The study will seek to improve the reliability of the estimation of return periods of very rare droughts.

(3) Exposure: propose how to improve a rapid damage assessment after a large-scale disaster – the case study of interdependent critical infrastructures during Hurricane Sandy. This study will propose a methodology of assessing large scale damages as well as the data requirement for it. (This work was published in the following literature: Haraguchi, M., & Kim, S. (2016). Critical infrastructure interdependence

in New York City during Hurricane Sandy. *International Journal of Disaster Resilience in the Built Environment*, 7(2), 133–143. http://doi.org/10.1108/IJDRBE-03-2015-0015)

(4) Vulnerability: propose how to improve supply chain resilience. This study will seek to show how to increase resilience in the private sector as well as how to improve methods of designing supply chains for resiliency. This work was published in the following two journals: (1) Haraguchi, M., Lall, U., & Watanabe, K. (2016). Building Private Sector Resilience: Directions After the 2015 Sendai Framework. *Journal of Disaster Research* Vol, 11(3), 535. (2) Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256-272.)

(5) Vulnerability: propose financial tools for rapid response and a rapid damage assessment method after catastrophic floods. This study will analyze how to prepare for catastrophic floods in Asia with financial tools,

such as index insurance and catastrophic bonds. Using remote sensing and ground level information, the study will also seek to improve existing damage assessment methodologies to assess large scale impacts.

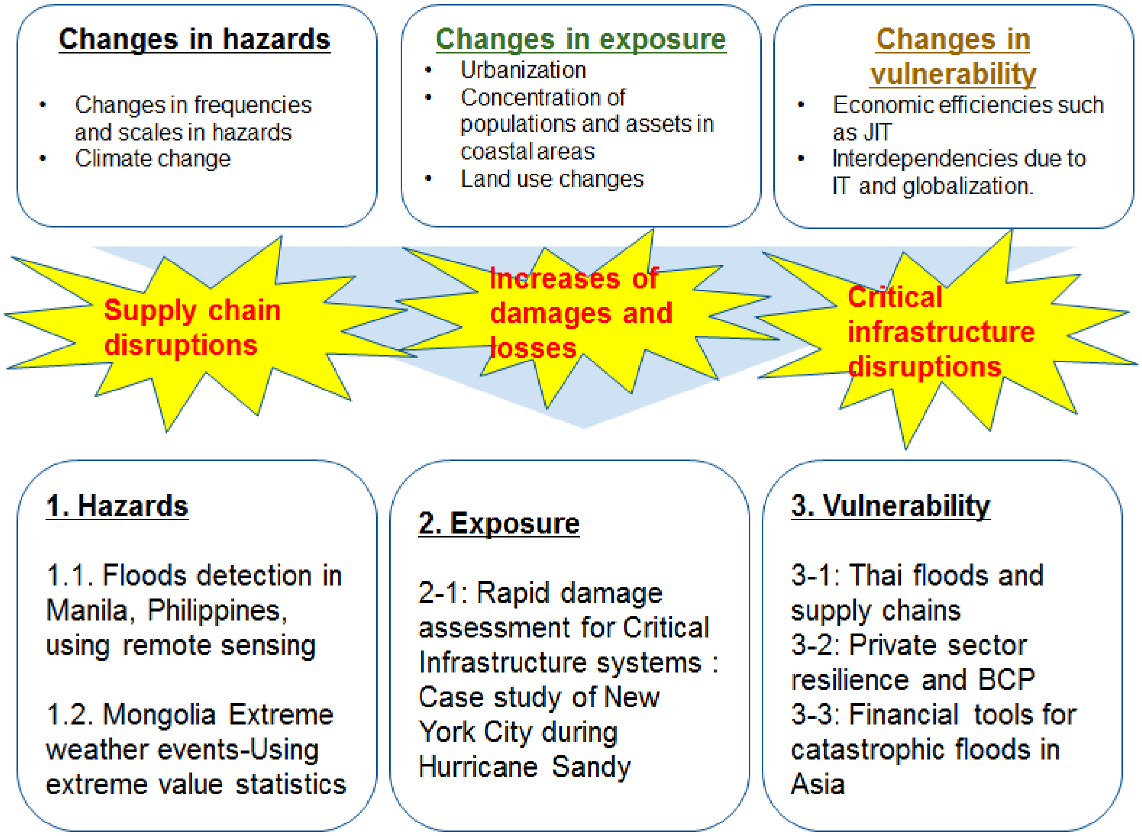


Figure 1-3: Schematics of each project of this study.

# CHAPTER 2. PREPARING FOR FLOODS IN MANILA, PHILIPPINES USING A DATA MINING TECHNIQUE -TOWARDS A FLOOD EARLY WARNING SYSTEM-


### Abstract

The goal of this paper is to develop a model to predict floods in Manila in the Philippines since Manila has experienced numerous flooding incidents for many years. This study attempted to find out if there were any relationships between flooding in Manila and remote-sensing environmental data, such as rainfall amounts and vegetation moisture using several data-mining techniques such as visualization, decision tree, and logistic regression. The study demonstrated that a model adding type of rainfall is better than one that only utilizes rainfall amounts or adds a vegetation index. Yet, the results did not show which is the better model, one that uses only rainfall type or the one that integrates all the information including rainfall type and vegetation index. Therefore, it is essential for local policy makers to comprehensively look at these indices and rainfall amounts to provide a flood prediction early-warning system in Manila.


## 2.1. Objectives

Floods have caused 62,000 deaths and displaced 610 million people in the world since 1985 according to the Dartmouth Flood Observatory. In particular, the Philippines is a typhoon-prone country. An average of 20 out of 36 tropical cyclones that develop over the Northwest Pacific basin per year cross the country. Metro Manila in the Philippines has also experienced numerous flooding incidents for many years. Within only the last five years, the area encountered seven incidents that caused casualties. Most notoriously, in September 2009, it experienced massive flooding which caused the deaths of 420 and resulted in 20,000 evacuees.

The objective of this research is to examine the relationship between flooding events in Metro Manila in the Philippines and remote-sensing environmental data. Urban flooding is a phenomenon caused by multiple factors such as large rainfall amount, flood-prone topography, inadequate infrastructure and water management, and rainfall anomalies. For this reason, it is challenging for policymakers at a local scale to mitigate and respond to flood risks. Therefore, it is important to unveil any relationships between flood occurrence and environmental indicators that can assist policy makers to prepare for the disasters in advance.

Previous studies discuss flooding in Manila. Bankoff (2003) argues that moderate flooding is produced by intense rainfall over an hour's duration often associated with tropical cyclones. Few studies, however, point out how to estimate actual precipitation amounts that lead to flooding in a rapid way, such as using remote sensing. For instance, Bankoff (2013) has not discovered a specific rainfall amount that leads to flooding in Manila. Muto et al (2012) also discusses flood occurrence mechanisms qualitatively, but without quantitative estimates. Therefore, a research question to be addressed here are of the following:

- ***How can floods be robustly identified under constraints of lacking data from stream gage sampling?***

The study will look at the indices in the following way: Dependent variable: flood occurrence, predictive variables: precipitation amount; type of rainfall; and vegetation indices. To examine the above a research question, the study will conduct the following tasks:

- **Task 1: To examine if there are any relationships between urban flooding and remote-sensing data (ex: rainfall and vegetation).** Firstly, the study will look at a time series of rainfall data and conducts an initial analysis with a baseline model.
- **Task 2: To examine if critical values, which are unique to Manila, can be identified and adequate models to predict floods there can be constructed.** Second, data mining techniques, such as visualization, decision tree, and cross-validated ridge regression, will be utilized to improve the baseline model to find better variables to predict floods in Manila. Model selection will be based on Akaike Information Criteria (AIC), which evaluates in-sampling modeling and on the ROC curve, which plots a false positive rate and true positive rate.

## 2.2. Study Design

The study attempts to develop the best-possible model to predict and prepare for floods using a data mining technique. First, the study looks at a time series of rainfall data and conducts an initial analysis with a baseline model. The study measures the intensity, volume, and duration of rainfall events. As the first analysis, the study used data mining techniques such as visualization and a decision tree to improve the baseline model and find better models to predict floods in Manila, Philippines. Then, the models incorporate types of rainfall events and a vegetation index. The model improvement will be measured by the following indicators (Table 2-1):

Table 2-1: Definition of 2 x 2 Contingency Matrix

| | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive | True Positive (TP) | False Positive (FP) |
| Predicted Negative | False Negative (FN) | True Negative (TN) |

*Precision= TP/(TP+FP)*

*Sensitivity= TP/(TP+FN)*

*Specificity= TN/(FP+TN)*

*Accuracy= (TP+TN)/(TP+FP+FN+TN)*

Since the accuracy is considered most comprehensive, the study will most value this indicator.

The second analysis of the study conducted cross-validated ridge regression to evaluate models. The models are evaluated through the AIC, BIC, and ROC curve.

## 2.3. Data, Background Information, and Preparation of the Analysis

A first attempt was made to examine an accurate rainfall amount that is observed at the ground level. However, nineteen out of twenty-two stations did not observe the time series of data, which prevents obtaining sufficient data to construct a model to prepare for floods. Thus, as a proxy for rainfall, this study used gridded satellite estimates, which are publicly available online. Additionally, vegetation indices, which measure ground moisture, were then used as additional indices. The reason for this is that ground moisture also partly influences the occurrence of floods, for example when the ground retains moisture from preceding rainfall events and then exceeds its capacity to further hold water. Therefore, although a single rainfall event may not necessarily induce floods, a series of rainfall events can lead to floods. In summary, the study will look at the indices in the following way:

*Dependent variable (DV): flood occurrence (binary)*

*Independent variables (IV): precipitation intensity, volume, and duration (numerical); type of rainfall (binary: tropical cyclone or not); and vegetation index (numerical).*

Specifically, data are taken from the following various sources.

*Spatial Domain*

This project considers a watershed that includes Metro Manila because of the assumption that the flooding is induced by precipitation that has fallen in the larger watershed. The spatial domain is 14 Degree of North to 16.4 Degree of North and 120.0833 Degree of East to 121.5833 Degree of East (Figure 2-1).

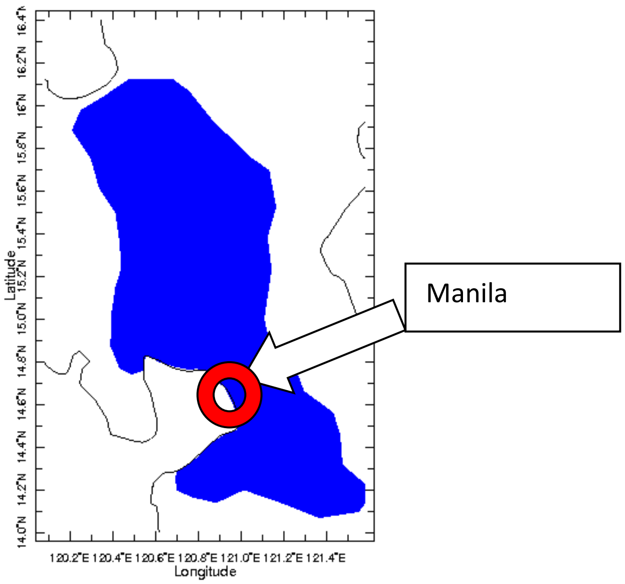


Figure 2-1: Map of the watershed ad Manila

## *Floods data (Dependent variable)*

Data of flood events were retrieved from the Dartmouth Flood Observatory. Seven flooding events were recorded in Manila areas since 2006 (Table 2-2). This study focused on the past five years. From the perspective of risk analysis, the flood risk is considered to be of less likelihood, but a large-impact event.

Table 2-2: Historical Flood Events Since 2006

| Starting Date | Ending Date | Main Cause | Number of Casualties | Number of Displaced People |
|---|---|---|---|---|
| 27-Sep-06 | 06-Oct-06 | Tropical cyclone | 260 | 250,000 |
| 8-Aug-07 | 13-Aug-07 | Tropical cyclone | 11 | 12,000 |
| 17-Aug-07 | 24-Aug-07 | Tropical cyclone | 42 | 600,000 |
| 16-Jul-09 | 18-Jul-09 | Tropical cyclone | 5 | n/a |
| 25-Sep-09 | 01-Oct-09 | Tropical storm Ketsana/Ondoy | 420 | 200,000 |
| 2-Oct-09 | 17-Oct-09 | Typhoon Parma | 438 | 40,000 |
| 30-Oct-09 | 04-Nov-09 | Tropical Storm Mirinae | n/a | 98 |

Dartmouth Flood Observatory (2011)[1].

### 2.3.1. Pre-assessment of Rainfall Data: Comparison between Station Data and Satellite Estimates

There are 22 stations in the area of focus. However, only three stations have full data for the periods between 2006–2009. They are Dagupan (IWMO#: 98325000, 120.3E 16.1N), Baguios (IWMO#: 98328000, 120.6E 16.4N), and Cabanatuan (IWMO#: 98330000, 120.97E 15.48N). The time period of January 2006 to October 2009 was used. As a satellite estimate, the study used the Climate Prediction Center Morphing Technique (CMORPH) updated daily by the National Oceanic and Atmospheric Administration (NOAA) at 0.25° latitude/longitude spatial resolution. The temporal resolution of this product is daily values in units of mm/hour. The results show that the gridded satellite estimates are quite reliable (Figure 2-2). Therefore, CMORPH was used in this study to estimate precipitation. Also, the study relates a flood event with rainfall events with two days prior to the flood event throughout the whole study.

In order to verify the gridded satellite estimates, the study calculated the mean error (bias), root mean square error (RMSE), and correlation in a comparison between a station monthly precipitation time series and a time series of the satellite precipitation estimates of the pixels that contain the station location. Station data can be drawn from the NOAA NCDC GHCN v2beta station precipitation dataset. The temporal resolution is monthly and is composed of 7280 station data.

[1] http://www.dartmouth.edu/~floods/Archives/index.html

Table 2-3: Satellite and Station Precipitation Error Statistics (mm/hours)

| Station Name | Station # | Location | CMORPH |
|---|---|---|---|
| Bias | | | |
| Dagupan Philippine | 98325000 | 16.1N 120.3E | -41.99982. |
| Baguio Philippine | 98328000 | 16.4N 120.6E | -31.93083. |
| Cabanatuan | 98330000 | 15.48N 120.97E | -53.34643. |
| RMSE | | | |
| Dagupan Philippine | 98325000 | 16.1N 120.3E | 124.896. |
| Baguio Philippine | 98328000 | 16.4N 120.6E | 134.2769. |
| Cabanatuan | 98330000 | 15.48N 120.97E | 191.6328. |
| Correlation | | | |
| Dagupan Philippine | 98325000 | 16.1N 120.3E | 0.9682999. |
| Baguio Philippines | 98328000 | 16.4N 120.6E | 0.9322107 |
| Cabanatuan | 98330000 | 15.48N 120.97E | 0.7597657 |

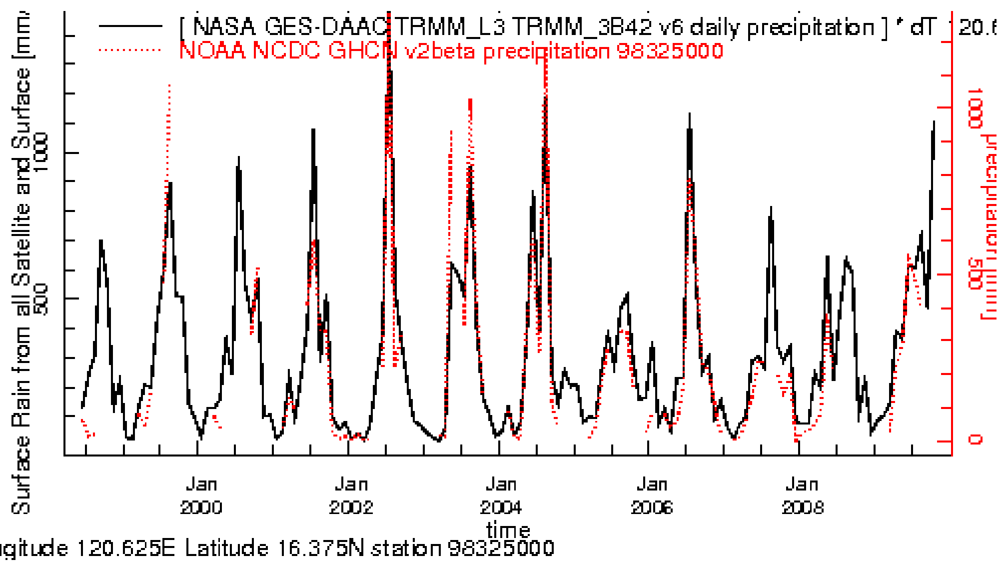


Figure 2-2: Comparison of Satellite and Station Precipitation

### 2.3.2. Vegetation Moisture

As a proxy for vegetation moisture, the Normalized Difference Vegetation Index (NDVI) offered by USGS's MODIS NDVI was employed in this study. NDVI has been used for many years to measure and monitor plant growth (vigor) and vegetation cover. The study considered using other indices such as the Enhanced Vegetation Index (EVI), which is also offered by USGS's MODIS and the Normalized Differenced Water Index (NDWI). However, since the preliminary analysis showed that these indices have strong correlations (0.98-0.99) over the study's time and spatial range, this study will use only NDVI.

NDVI is derived from measurements made by the USGS.LandDAAC.MODIS .version_005 .SEAS . reflectance. The time resolution is 16-day daily and special resolution is 250 meters. The number of data and locations that are used in this study are summarized in Table A-1 in the Appendix.

## 2.4. Exploratory Analysis

To discover critical values that cause floods and construct a prediction model of floods in Metro Manila, the study firstly plotted and compared time series data of a weighted-average daily precipitation values from CMOPRH for 14 flood-causing rainfall events in the area of focus (Figure 2-3). The time series of daily precipitation was plotted over the period of January 2006 – December 2009.

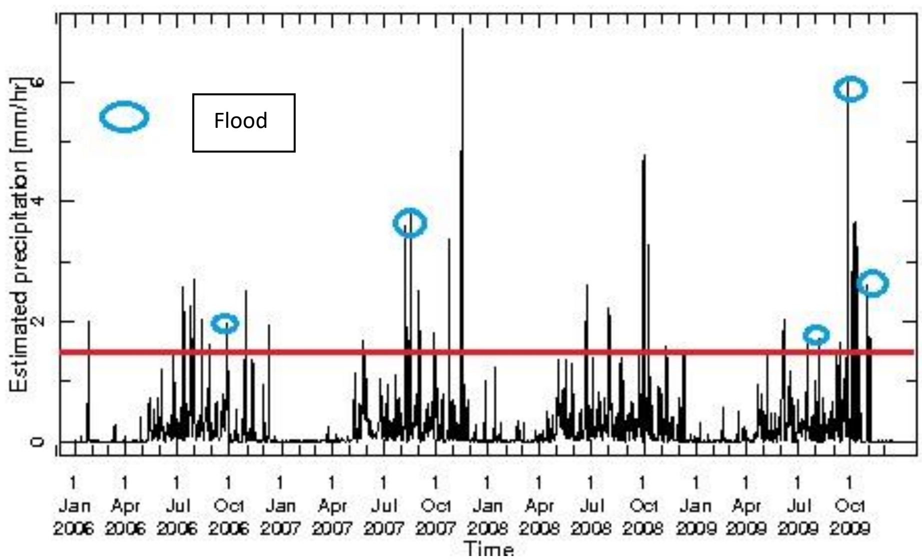


Figure 2-3: Initial Analysis - Every Flood Occurs over 1.5 mm/hour

Since the remote-sensing data records a very small amount of rainfall, the study cut off the value below 0.5mm/hour. Then, the study calculated one successive day of rainfall to one rainfall event. Thereafter, the volume and duration of each rainfall event has been calculated. During the period of the seven flood events, it can be estimated from the CMOPRH that every flood event was accompanied by more than 1.5 mm/hour of rainfall intensity, which can be considered as a potential critical value that could indicate flood events in Manila. Also, most of the floods are related with 20mm/event of rainfall volume and two days/event of rainfall duration (Table 2-4).

Table 2-4: Flood Events and Associated Rainfall Intensity, Volume, and Duration

| Flood Starting Date | Flood Ending Date | Related Rainfall Event(s) | Highest Precipitation (mm/hour) | Rainfall Volume (mm/event) | Rainfall Duration (days/event) |
|---|---|---|---|---|---|
| 27-Sep-06 | 06-Oct-06 | Sept 27-28 | 1.16 | 46.64 | 2 |
| 8-Aug-07 | 13-Aug-07 | August 5 | 0.84 | 20.07 | 1 |
| | | August 7-9 | 1.86 | 96.70 | 3 |
| 17-Aug-07 | 24-Aug-07 | August 14-15 | 1.55 | 50.02 | 2 |
| | | August 17 | 2.25 | 54.02 | 1 |
| | | August 20 | 0.88 | 21.08 | 1 |
| | | August 22-24 | 1.48 | 89.69 | 3 |
| 16-Jul-09 | 18-Jul-09 | July 16-July17 | 2.17 | 68.22 | 2 |
| 25-Sep-09 | 01-Oct-09 | Sept 22- Sept23 | 2.11 | 74.88 | 2 |
| | | Sept 25 | 1.83 | 43.90 | 1 |
| | | Sept 27 | 0.58 | 13.93 | 1 |
| 2-Oct-09 | 17-Oct-09 | Oct 2- Oct 4 | 6.86 | 215.58 | 3 |
| | | Oct 7- Oct8 | 12.34 | 376.88 | 2 |
| 30-Oct-09 | 04-Nov-09 | Oct 30 | 0.81 | 19.41 | 1 |

2 days lag

As seen in Table 2-5, the reliability of 1.5 mm/hour of rainfall intensity is not high (e.g., accuracy is 69%). Tables Table 2-6 and Table 2-7 show that the critical value of 2 days duration of one rainfall event has more accuracy than that of the volume (20mm/event). Therefore, none of these three models can provide an accurate forecast. In addition, the possibilities of false negatives can have devastating effects (i.e. if the prediction is wrong and then a flood occurs). Thus, it is necessary to improve the model. Since the highest rainfall intensity of 1.5 mm/hour has the largest accuracy, this study will continue to use this value. Then, using this value of 1.5 mm/hour, the study found rainfall events that did not cause flooding in Manila. Using a value of 1.5 mm/hour of rainfall is considered as the baseline model in this study and is compared with other models in terms of how other data will improve the model.

Table 2-5: Matrix of Predicted Flood or True Flood Using Rainfall Intensity

| Highest rainfall intensity (mm/hour) | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive (>=1.5 mm/hour) | 9 | 35 |
| Predicted Negative (<1.5 mm/hour) | 6 | 81 |
| Precision | 20% | |
| Sensitivity | 60% | |
| Specificity | 70% | |
| Accuracy | 69% | |

Table 2-6: Matrix of Predicted Flood or True Flood Using Rainfall Volume

| Volume (mm/event) | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive (>20.0mm/event) | 12 | 82 |
| Predicted Negative (<20.0mm/event) | 2 | 35 |
| Precision | 13% | |
| Sensitivity | 86% | |
| Specificity | 30% | |
| Accuracy | 36% | |

Table 2-7: Matrix of Predicted Flood or True Flood Using Rainfall Duration

| Duration (days/event) | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive (>=2 days) | 8 | 40 |
| Predicted Negative (<2 days) | 6 | 77 |
| Precision | 17% | |
| Sensitivity | 57% | |
| Specificity | 66% | |
| Accuracy | 65% | |

## 2.5. Visualization and Decision Tree

### 2.5.1. Methodologies to Compare Different Models

With this critical value in mind, the study looked at rainfall events that were not associated with floods in Manila, even if they were over the 1.5 mm/hour critical value. The results from CMORPH, with weighted average and over all areas of the watershed, are depicted in Figures A-1 to A-10 in the Appendix. There were 35 rainfall events of 1.5 mm/hour or greater that were not associated with flooding. Thus, the study tried to find other data to be added using visualization and a decision tree analysis. The models from the decision trees were evaluated in terms of sensitivity, precision, specificity, and accuracy. This method compares performance in the following models:

Model 1 (Baseline): 1.5mm/hour of rainfall intensity

Model 2: Adding type of rainfall to the baseline

Model3: Adding NDVI to the baseline

Model4: Adding type of rainfall and NDVI to the baseline

### 2.5.2. Model 2: Adding Type of Rainfall (Tropical Cyclone or Not)

*Visualization*

First, the type of rainfall was then added from UNISYS for every rainfall event that was more than 1.5 mm/hour. Since the website of UNISYS provides information regarding storms such as hurricanes and typhoons from all over the world, the study tried to determine what kind of tropical cyclones were associated with each rainfall event with over 1.5 mm/hour of rainfall. Figures 3-1 to 3-10 and Table 2-2 show that floods were always associated with some type of tropical cyclones, while 81% of rainfall events with greater than 1.5 mm/hour rainfall that did not cause floods were not related with any tropical cyclone.

*Time Series are shown in Figures A-1 to A-10 of the Appendix*

Based on the above observation, the study added a binary value to the decision tree (Figure 2-4) and constructed a decision tree with a size of 3. By adding this binary value, the mode accuracy improved to 88% and specificity to 94% (Table 2-8). Consequently, if rainfall events are tropical cyclones, more attention should be paid to prepare for floods. However, 36% in sensitivity is considered very low given its catastrophic impact. Therefore, the study will look at adding another data type: vegetation index.

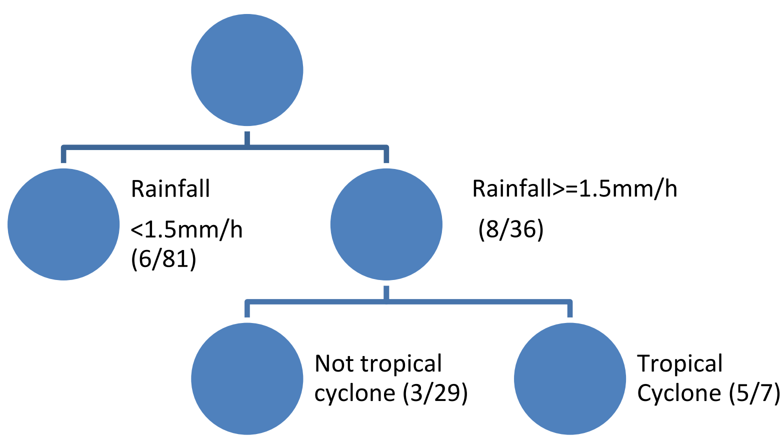


Figure 2-4: Decision tree of adding type of rainfall. The numbers in parenthesis indicate the ratio of the number of flood occurrence to the number of the occurrence without actual floods.

Table 2-8: 2 x 2 Matrix of Predicted Flood or True Flood Using Type of Rainfall

| Highest Intensity and Rainfall Type | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive | 5 | 7 |
| Predicted Negative | 9 | 110 |
| Precision | 42% | |
| Sensitivity | 36% | |
| Specificity | 94% | |
| Accuracy | 88% | |

### 2.5.3. Model 3: Adding Vegetation Greenness and Moisture Index

Since only the rainfall amount and type do not provide a reliable value that determines whether floods would occur or not, the study also conducted vegetation analysis using NDVI. This index was plotted for both the watershed areas of focus (120.0833E 121.5833E, 14N - 16.4N) and for smaller areas surrounding Manila (121E-121.5E, 14N-15N). The study looked at the mapping, decision analysis using vegetation indices, and the time series of these indices over the studied period of January 2006 – March 2011.

#### *Mapping*

It is clear that every time a flood occurred, NDVI indicated that soil moistures were high over the region (for example, in Fig. 10 the red region is more likely to have floods.) However, NDVI was high even when floods did not occur (for example, Figure 2-5). Therefore, there were no significant differences in the NDVI map visualization for determining a critical metric to project a flood.

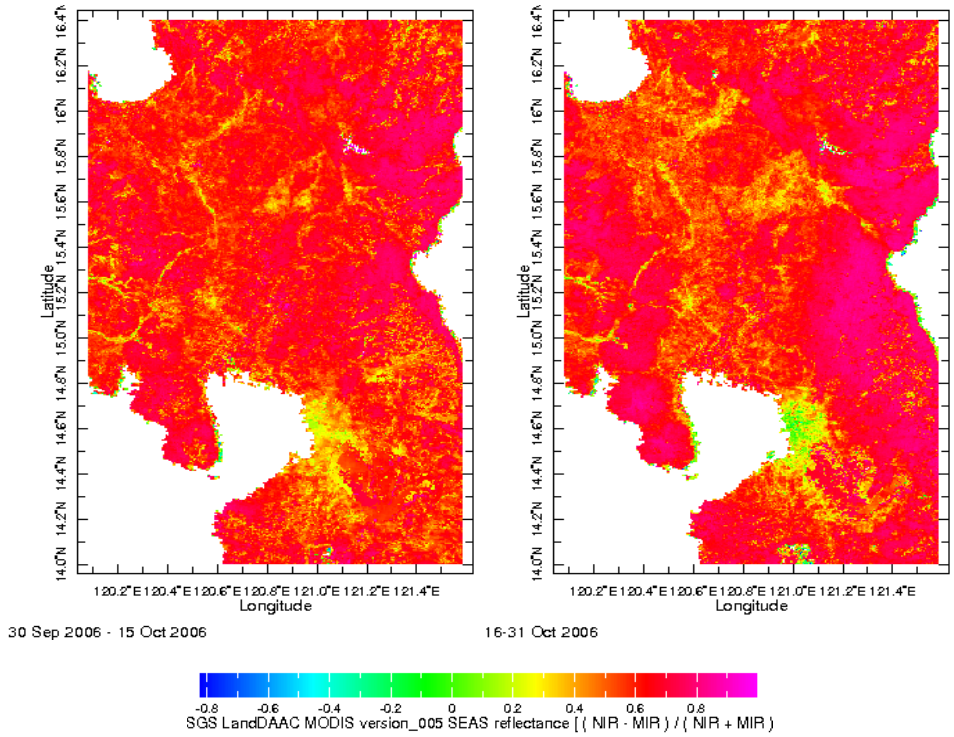


Figure 2-5 (a): NDVI during floods. Figure 8 (b) NDVI during no floods

As can be seen in Figure 2-6 and Table 2-9, the index will improve the accuracy and specificity if added. More than a 0.5 NDVI value has an accuracy of 73% and specificity 74%. However, the accuracy of this model has declined to 73% from 88% of the one that uses the types of rainfall. Thus, this index as a single source cannot provide a critical value to provide early warning for floods in Manila.

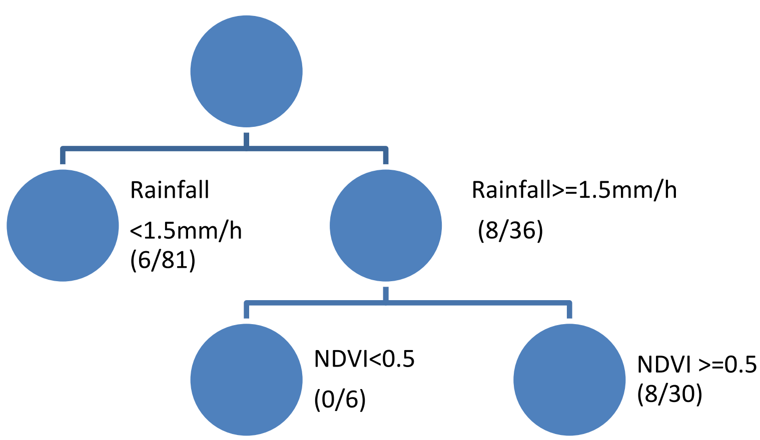


Figure 2-6: Decision tree

Table 2-9: Matrix of Predicted Flood or True Flood Using NDVI

| NDVI>=0.5 | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive | 8 | 30 |
| Predicted Negative | 6 | 87 |
| Precision | 21% | |
| Sensitivity | 57% | |
| Specificity | 74% | |
| Accuracy | 73% | |

### 2.5.4. Model 4: Integration of Rainfall Amount, Rainfall Type, and Vegetation Indices

Comparing these two decision trees, adding information on type of rainfall improved largely accuracy and specificity while adding the vegetation index improved sensitivity. As can be seen, the model with added type of rainfall and the vegetation index performs best in terms of accuracy, precision, specificity (Table 2-10 and Table 2-11). In terms of accuracy, the study places the most value in Models 2 and 4. However, given the devastating effect of false negative, shown in the value of sensitivity, a policy maker should also look at volume of a rainfall event whose value of sensitivity is high (86%).

Table 2-10: 2 x 2 Matrix of Predicted Flood or True Flood Using Rainfall type and NDVI

| Type of rain Every indices | Actual Positive (=Flood occurred) | Actual Negative (=Flood did not occur) |
|---|---|---|
| Predicted Positive | 5 | 7 |
| Predicted Negative | 9 | 110 |
| Precision | 42% | |
| Sensitivity | 36% | |
| Specificity | 94% | |
| Accuracy | 88% | |

Table 2-11: Summary of the Evaluation Values for Each Model

| | Accuracy | Precision | Sensitivity | Specificity |
|---|---|---|---|---|
| Baseline 1.5 mm/h | 69% | 20% | 60% | 70% |
| Volume >20 | 36% | 13% | 86% | 36% |
| Duration >=2 | 65% | 17% | 57% | 66% |
| Model 2: Adding type of rainfall | 88% | 42% | 36% | 94% |
| Model 3: Adding NDVI | 73% | 21% | 57% | 73% |
| Model 4: Adding type of rainfall and NDVI | 88% | 42% | 36% | 94% |

### 2.5.5. Times Series Visualization

Next, the study looked at the time series of NDVI from January 2006 – March 2011 (Fig. A-9 in the Appendix). There are weak tendencies in the high vegetation index (NDVI) before flooding events (indicated by red vertical lines in Fig. A-9 in the Appendix). However, there continues to be no clear differences in the indices between the rainfall events leading to floods with more than 1.5 mm/hour rainfall and the ones that did not cause flood events (indicated by green vertical lines in Fig. A-9 in the Appendix). Hence, it is critical to look at various indices when attempting to predict floods.

## 2.6. Cross-validated Ridge Regression

To predict a response variable, the study next conducted a logistic regression using cross validation. First, data was split into training and test sets using an 80/20 split, and then conducting logistic regressions for 4 models:

(1) Baseline model (IV: Rainfall amount)

(2) Adding type of rainfall to the baseline model (IV: rainfall amount, type of rainfall)

(3) Adding vegetation indices to the baseline (IV: rainfall amount, NDVI)

(4) Adding both types of rainfall and vegetation indices (IV: rainfall amount, type of rainfall, NDVI).

A comparison of the AIC and BIC, which evaluates in-sample modeling, Table 2-12 indicates that the best models are Model 2 and Model 4.

Table 2-12: AIC and BIC Values for Each Model

| Model | AIC | BIC |
|---|---|---|
| (1) Baseline model (IV: Rainfall amount) | 351.8 | 392.2 |
| (2) Adding type of rainfall to the baseline model (IV: rainfall amount, type of rainfall) | 279.4 | 320.7 |
| (3) Adding vegetation indices to the baseline (IV: rainfall amount, NDVI) | 347.5 | 396.9 |
| (4) Adding both type of rainfall and vegetation indices (IV: rainfall amount, type of rainfall, NDVI) | 281.4 | 327.7 |

The study then went on to use these models to make predictions for the test set. These models gave a probability of flood for each observation in the test set. A False Positive Rate (1-specificity) and True

Positive Rate (sensitivity) were plotted as ROC curves in Figure 2-7. As can be seen, there is a clear indication that both Models 2 and 4 show better performances in the test set than the Models 1 or 3. Yet, there were no clear differences between Models 2 and 4. This result is consistent with the result that is gained through the previous decision tree analysis. Namely, Model 2, which uses rainfall intensity and types, and Model 4, which utilizes all rainfall intensity, type, and vegetation index, can predict most accurately.

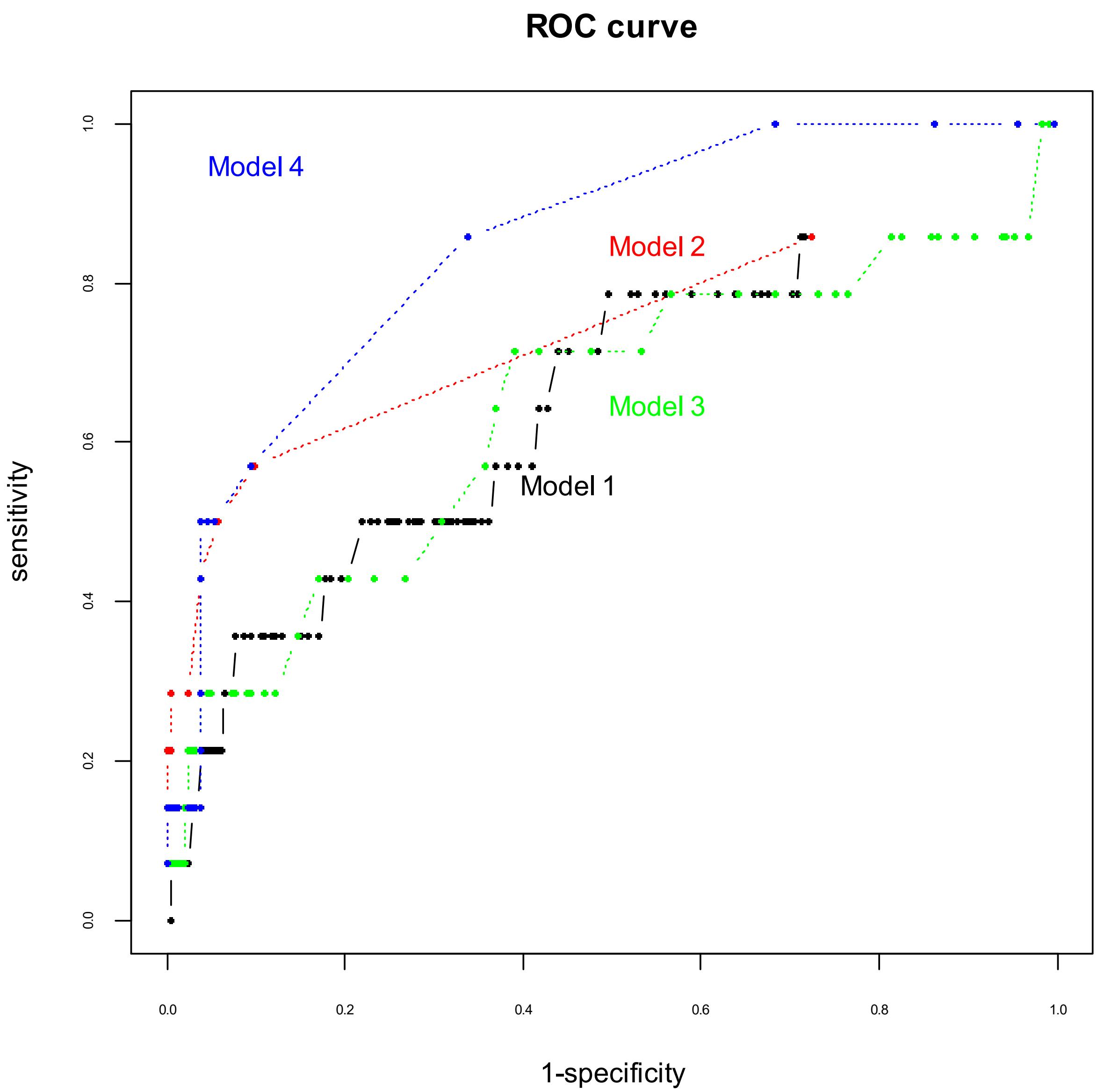


Figure 2-7: ROC curve

## 2.7. Conclusions and Study Limitations

This study attempted to find out if there were any relationships between flooding and remote-sensing environmental data, such as rainfall amount and vegetation moisture using several data-mining techniques such as visualization, decision tree, and logistic regression. The initial analysis of rainfall data indicated that most flooding events had more than 1.5 mm/hour of rainfall, 20 mm/event of rainfall volume, and 2 days/event of rainfall duration over the studied watershed area. Yet, the study also discovered that many rainfall events of 1.5 mm/hour or greater did not cause floods.

Thus, to improve the performance of the prediction models, the study also found what types of rainfall were associated with floods. Floods were always associated with tropical cyclones. In contrast, rainfall events of more than 1.5 mm/hour that did not lead to floods were unlinked at 81% with tropical cyclones.

The study also tried to find any relationships between vegetation moisture and greenness and flood events. When there were floods, there were tendencies for higher indices of NDVI. The decision tree shows that accuracy and specificity improved because of these indices. However, the study did not find a single critical value of these indices that can provide a reliable indication for the early prediction of floods.

In contrast, as the result of decision trees, the classification rate and other indices such as sensitivity and specificity show that the best prediction models are the one that uses rainfall types, and the one that integrates rainfall amount, rainfall type, and vegetation indices.

This result was also supported by findings from the cross-validated logistic regression. The study demonstrated clearly that a model adding rainfall types is better than one that only utilizes rainfall amount or adds the vegetation index. Yet, the results did not show which is better, the model between one that uses only rainfall type or the one that integrates all the information including rainfall type and various vegetation moisture indices.

In summary, it is essential for local policy makers to comprehensively look at these indices and rainfall intensity, volume, and duration to provide a flood prediction early-warning system in Manila. Local policy makers must consider rainfall amount and duration, type of rainfall, and vegetation indices along with other important indicators such as water height at local rivers and dams.

As with any study, there are some limitations. First, it considers only the time series of rainfall dated from January 2006 to December 2009 because of the lack of data on floods in Manila. With current data gathering now in progress, future researchers will have a broader time domain to examine. Second, this study only examined three types of predictors (rainfall amount, rainfall type, and three vegetation indices). Future work should consider other factors that cause floods in an urban area, such as any human-made and natural infrastructure considerations.

# CHAPTER 3. RISK ANALYSIS FOR DZUD IN MONGOLIA

## Abstract

Mass livestock mortality, known as dzud, causes significant socioeconomic problems in Mongolia. Existing studies argue that the frequency and intensity of dzud are rising due to the combined effects of climate change and variability, and socioeconomic dynamics. However, few studies investigate risk analysis for dzud and the recurrence of dzud using a long climatic record. Given that climate is a significant driver of the occurrence of dzud and there is a signal of cyclic climate regimes at the interannual to centurial scales, the risk analysis of dzud from the perspective of climate regimes is critical. This study aims to fill the gaps in technical knowledge about the recurrence probability of dzud by estimating the return levels of relevant climatic variables. Our study uses a long-term proxy of droughts, the tree-ring reconstructed Palmer Drought Severity Index (PDSI) between 1700-present. Our study also simulates winter minimum temperature in Mongolia from the instrumental data in Siberia, including data from the early 19th century. Based on these data, we estimate the distributions of summer drought conditions and winter minimum temperature and their return levels in Mongolia for risk analysis. Based on the Generalized Extreme Value (GEV), the return levels of drought conditions are changing over time and its variabilities are increasing for all the regions. Furthermore, this study finds that the median of 100-year return levels of the winter minimum temperature in Mongolia is -26.08 Celsius degrees for the Southwest, -27.99 Celsius degrees for the Northwest, and -25.31 Celsius degrees for the East. These return period estimates will fill in the gaps between studies on the meteorological characteristics and socioeconomic impacts on livestock populations, and the design of the livestock index insurance.

## 3.1 Introduction

Mass livestock mortality induced by dry summers followed by unusually cold and/or snowy winters, known as dzud, causes problems for pastoral herding and the economy in Mongolia.[2] A total of 20 million livestock died of climate extremes from 2000-2002, and 2009-2010 (Rao et al., 2015). In the 2009-2010 dzud alone,

[2] Dzud is Russian way of notation, and it is locally written as "zud" in Mongolia.

approximately 20% of the country's livestock population died, which affected 769,000 people, 28% of the population in Mongolia (ReliefWeb, 2010).

The occurrence of dzud is complex. Increased population of livestock along with other land use changes such as urbanization and mining are viewed as a major cause of the decline in pasture in the region (Bat-Oyun, Shinoda, Cheng, & Purevdorj, 2016; Berger, Buuveibaatar, & Mishra, 2013; Hilker, Natsagdorj, Waring, Lyapustin, & Wang, 2014). Along with other socio-economic factors, such as overgrazing, livestock mortality is caused and exacerbated by the following climate factors: summer drought, heavy snow, and high winds in concurrence with extreme cold winter temperature (Morinaga, Tian, & Shinoda, 2003). Livestock mortality is strongly associated with winter (November – February) temperatures and prior summer (July – September) droughts and precipitation (Rao et al., 2015; Tachiiri, Shinoda, Klinkenberg, & Morinaga, 2008b). For example, Rao et al. (2015) showed that the model based on winter temperature, summer drought, summer precipitation, and summer potential evapotranspiration explains 48.4% of the entire variability of mortality. Extreme cold temperature as well as exposure to storms or high winds cause livestock to freeze to death while heavy snow, ice or drought, prevent livestock from grazing and accessing fodder, which results in weakening immune system response and starvation (Begzsuren, Ellis, Ojima, Coughenour, & Chuluun, 2004; Fernández-Giménez, Batkhishig, & Batbuyan, 2012; Morinaga et al., 2003; Rao et al., 2015). In addition to extreme winter temperature and snowfall, summer drought is an important driver because droughts deteriorate grazing and prevent livestock from surviving during severe winters(Begzsuren et al., 2004; Rao et al., 2015; Tachiiri, Shinoda, Klinkenberg, & Morinaga, 2008). Therefore, in this paper, we use the term dzud to refer to livestock mortality, especially the one caused by summer droughts followed by extreme cold and snowy winters.

Understanding mechanisms and impacts of dzud and climate extremes has wider implications for sustainability in rangelands, which account for 50% of Earth's land surface, where 40% of the world's populations reside (Fernández-Giménez et al., 2012; Reynolds et al., 2007). A better understanding of the climate drivers of dzud and extreme events is also critical for preventive and responsive measures, such as weather index insurance. Weather index insurance recently became widely available, and its indemnities are paid based on realizations of a weather index such as rainfall and temperature that are expected to be highly correlated with actual losses, rather than on actual losses experienced by the policyholder (Barnett & Mahul, 2007). The index-based livestock insurance program (IBLIP) was institutionalized in 2014 to respond to the extreme climate disasters by the Government of Mongolia with help from the World Bank (Mahul, Belete, & Goodland, 2009; Mahul & Skees, 2007; Skees & Enkh-Amgalan, 2002).

Few studies have performed risk analysis of dzud using long-term climate data. One reason for this is that there are few long-term instrumental records of climate in the region, and the records that do exist are often not continuous and contain missing data. Though historical documents record the occurrence of dzud from the 19th century (Regional Resource Centre for Asia and the Pacific, 2002), changes in climate in Mongolia have been observed in instrumental records only since 1940 (Batima P, Natsagdorj L, Gombluudev P, & Erdenetsetseg B, 2005). Additionally studies concluded that the frequency of dzud has increased since 1950 (Fernández-Giménez et al., 2012; Middleton, Rueff, Sternberg, Batbuyan, & Thomas, 2015) and that it is expected to increase with future climatic changes (Bayasgalan et al., 2009). Natsagdorj & Dulamsuren (2001) show that the trends of drought and the dzud index, estimated by normalized monthly temperature and precipitation, are increasing. However, these studies are based on observational data of dzud, which are available only from about 1940. It is critical to extend the time horizon in order to improve the reliability of the return period estimation of catastrophic dzud. Long-term climate proxies, such as tree rings, have the potential to do so by deriving recurrence periods of dzud and climate extremes, especially to improve index insurance products (Bell et al., 2013). Yet, one of the challenges of improving the reliability of recurrence estimations is the lack of scientific understanding of the historical trends of past climate events due to the short meteorological record (Mahul & Stutley, 2010; McSharry, 2014; Rao et al., 2015).

To improve risk analysis of dzud, the investigation of extreme distributions of climate extremes is critical. D'Arrigo et al. (2001) inferred using millennial length tree-ring data that temperatures in Mongolia in the late 1990s and early 2000s were extraordinarily. Based on a well-calibrated and verified millennial-length tree-ring reconstruction of summer temperatures, Davi et al. (2015) places the recent warming trend since the 1990s to be anomalous in the long-term context in Mongolia. In addition, Davi et al. (2010) conducted spectral analysis to discover the periodicity of droughts in Mongolia by using tree-ring reconstructed Palmer Drought Severity Index (PDSI). However, these studies do not estimate distributions of extreme climatic events or improve the reliability of the estimation of return periods of dzud for risk analysis. Here, we use the term "risk analysis" to refer to the analysis of the probability of an extreme event whose consequences could be substantial (Rootzén & Katz, 2013), but not the analysis where risk commonly refers to the combination of the probability of an event and its associated expected losses.

*Objectives of the study*

Hence, the objective of this study is to conduct risk analysis for the climatic variables that cause dzud, namely summer drought followed by extreme cold temperature and snowfall, in Mongolia while attempting to improve the reliability of the return period estimation of dzud utilizing proxies and historical data on climatic variables. The study also explores the implications of the risk analysis and return period estimation for index insurance. To address these objectives, a research question is posed:

- ***How can the reliability of the return period estimation of climate extremes be improved?***

There are two important climatic variables to predict dzud: drought conditions and winter temperatures (Lall, Devineni, & Kaheil, 2016; Rao et al., 2015). Particularly, this study estimates return periods of extreme drought conditions, by using tree-ring reconstructed PDSI from the Monsoon Asia Drought Atlas or MADA (Cook et al., 2010). It also estimates return periods of extreme cold temperatures in Mongolia. Since temperature data in Mongolia is only available from the early 20th century, we simulate them from meteorological data in neighboring Siberia through a statistical model that we develop. Tree-ring based temperature reconstruction in the region is typically for the growing season and does not capture winter temperatures so are not used in this analysis. Existing research conducted spectral analysis of extreme cold weather events in Mongolia (N. Davi et al., 2010; N. K. Davi et al., 2015), but did not estimate distributions or analyze return periods back to 1700.

Even though dzud locally means high livestock mortality in Mongolia (Fernández-Giménez et al., 2012; Morinaga et al., 2003), this study uses climate variables for risk analysis, not on mortality rate itself for the following reason. Using mortality assumes that the size of the population does not matter if mortality rate is used. However, this is based on a questionable assumption that changes in the livestock population are not associated with changes in other socio-economic factors, such as shortage of food supply, which are induced by non-climate factors. In reality, other socio-economic factors also determine livestock herding.

The total number of livestock and its density (per square kilometer) drastically increased after a transition to private ownership in 1990s (Johnson, Sheehy, Miller, & Damiran, 2006; Rao et al., 2015; Reading, Bedunah, & Amgalanbaatar, 2006). The increasing livestock population results in overgrazing, emaciating the grassland, which leads to limiting its carrying capacity for livestock and finally causing the high mortality (Bat-Oyun et al., 2016; Berger et al., 2013; Hilker et al., 2014; Liu et al., 2013).

In order to estimate a return level of a rare event, extreme value theory (EVT) is useful (Cheng et al., 2014; Katz, Parlange, & Naveau, 2002). EVT informs us how to extrapolate a rare event which has not been experienced for a long time from existing observational data with a short record. This enables us to formulate a risk management strategy by deriving a distribution of extreme weather events and estimating a possible extreme value for the future. There are two main approaches in EVT: Block maximum approach and threshold approach, which will be described later. To explore the above research questions, the study will conduct the following tasks.

- **Task 1: Estimate return periods of extreme drought conditions by using reconstructed Palmer Drought Severity Index (PDSI) based on extreme value theories.** In order to estimate return periods of extreme drought conditions, tree-ring reconstructed Palmer Drought Severity Index (PDSI) and extreme value theories are used. Block maximum approach by using Generalized Extreme Value (GEV) distributions and threshold approach by using Generalized Pareto Distributions (GPD) will be used while checking the stationarity of the data. If it is not stationary, the non-stationary extreme value technique will be used.
- **Task 2: Estimate return periods of extreme cold temperatures in Mongolia by using instrumental data from Siberia.** First, winter temperatures in Mongolia will be simulated by using instrumental temperature data from Siberia. By using the simulated winter temperature in Mongolia, return periods of extreme cold temperature during winters will be estimated.

Conventionally, in estimating return periods, a stationarity process is assumed. Here, we consider the extension of the record by explicit dependence on climate proxies. Of course, this gives us a stationary return period, which is useful for risk assessment and writing a parametric insurance policy. However, we also examine how the return periods may change over time due to slowly and systematically changing climate conditions, persistence in the PDSI, or other climate records. Exploring the nonstationary approach to return period and risk opens “many opportunities” (Salas & Obeysekera, 2014). This has the advantage of reducing the bias in the near term projection, assessment of the return period, and recurrence interval associated with the event. Given this information, either the parametric insurance could be repriced up or down, or preparatory actions could be undertaken.

The study also explores the utility of using long-term climate proxies in the context of index insurance. In general, the index used for index insurance must be scientifically objective and easily measurable. Though IBLIP uses mortality rate as the index, this study will explore if climate proxies have the potential to improve the design of the IBLIP.

## 3.2 Data and Methodology

### 3.2.1. Data and Preliminary Analysis

#### *Tree-ring Reconstructed PDSI*

PDSI is a standardized index that ranges from -10 (dry) and +10 (wet) based on a water balance model, accounting for precipitation, evaporation, and soil moisture storage (Cook et al., 2010; Dai, Trenberth, & Qian, 2004; Palmer, 1965). In this study, tree-ring reconstructed PDSI values from 1700 to 2013 are taken from Monsoon Asia Drought Atlas (MADA)(Cook et al., 2010). MADA is a seasonally resolved gridded spatial reconstruction of drought and pluvials in monsoon Asia over the last 700 years, derived from a network of tree-ring chronologies (Cook et al., 2010). The benefit of using the three regional series is to capture smaller-scale regional details of known droughts because it is based only on the chronologies identified from the principal component analysis (Cook et al., 2010). MADA can also reveal the occurrence and severity of previously unknown monsoon droughts (Cook et al., 2010). We consider three regions (Northwest, Southwest, and East Mongolia) in Mongolia based on clusters proposed by Kaheil and Lall (Figure 3-3). These clusters are based on the mortality index at the soum (county) level from 1972 to 2010, using hierarchical clustering, which were adjusted with the spatial patterns of the Mongolian topography, climate zones, and mean precipitation in growing seasons. It is reasonable to use these clusters because the objective of the study is to improve risk analysis of Dzud and mortality of livestock in Mongolia.

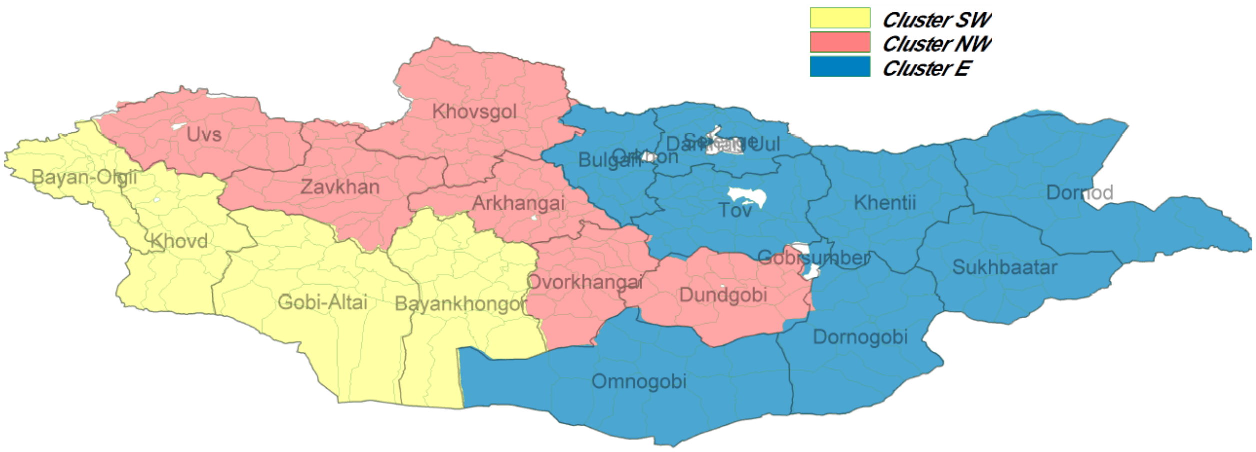


Figure 3-1 Spatial Clusters of Mortality Index based on 1972-2010 soum level mortality indices

The correlation in PDSI values from 1700 to 2013 between three clusters is shown in Table 3-1. The Mann-Kendall trend test is used to examine the trends of the PDSI data (Kendall, 1948; Mann, 1945). The Mann-Kendall test shows that there are no monotonic trends in the PDSI data for all clusters (Table 3-1). Yet, times series of tree-ring reconstructed PDSI by clusters show that there is significant centennial- scale variability, which is important to consider since they suggest that there are persistent regimes that can last for decades to century time scales (Figure 3-2, Figure 3-3, Figure 3-4). Though these may occur randomly or reflect systematic cyclical behavior, their consideration in a risk management strategy is critical.

Table 3-1: Correlations coefficients of PDSI values from 1700 to 2013 between the three clusters

| | Pearson Correlation Coefficients | Mann-Kendall value |
|---|---:|---:|
| Southwest and Northwest | 0.78 | 0.0004 |
| Southwest and East | 0.50 | 0.0002 |
| Northwest and East | 0.69 | -0.0026 |

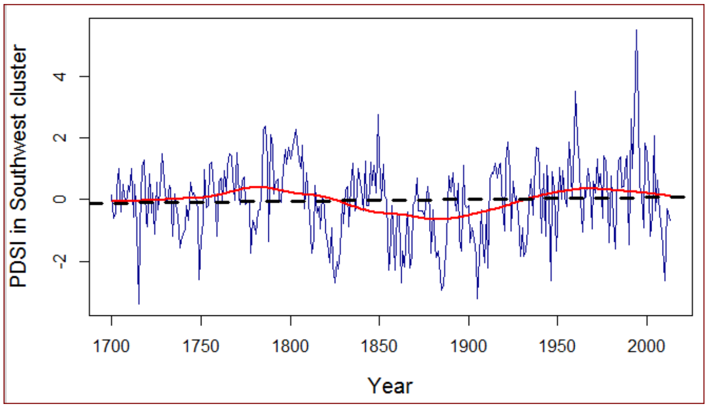


Figure 3-2: Time series of tree-ring reconstructed PDSI in the Southwest cluster. The horizontal line represents the estimated line of the regression of PDSI on year, and the red curve represents a lowess smooth of the data.

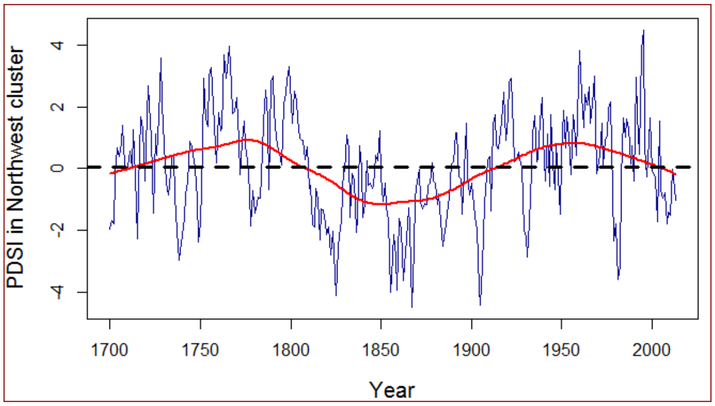


Figure 3-3: Time series of tree-ring reconstructed PDSI in the Northwest cluster. The horizontal line represents the estimated line of the regression of PDSI on year, and the red curve represents a lowess smooth of the data.

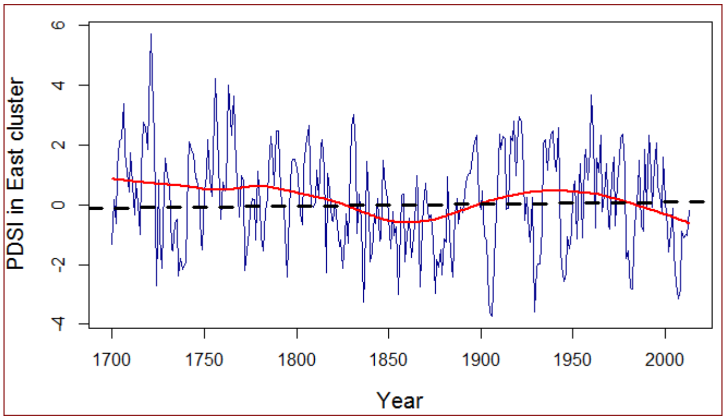


Figure 3-4: Time series of tree-ring reconstructed PDSI in the East cluster. The horizontal line represents the estimated line of the regression of PDSI on year, and the red curve represents a lowess smooth of the data.

The autocorrelation function (ACF) and Partial ACF of all the regions show that there are significant autocorrelations in the PDSI data in all clusters (Figure 3-5, Figure 3-6). The development of a time series simulation model that uses these long lead correlations would help inform the risk analysis associated with the persistent regimes identified earlier. Thus, Autoregressive–Moving-Average (ARMA) models with different orders are evaluated based on BIC. The order of the best ARIMA models in each cluster is (3,0,0) for the Southwest, (1,0,2) for the Northwest, and (1,0,0) for the East. These ARIMA models will be used later to forecast the effective return periods of droughts.

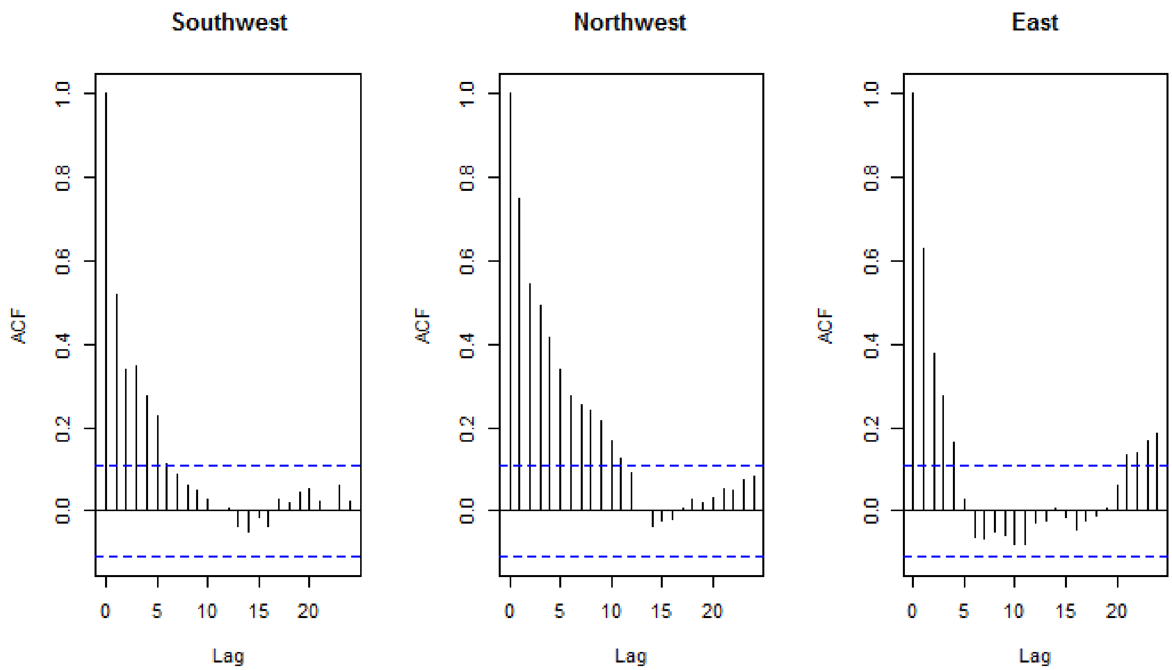


Figure 3-5: ACF of the tree-ring reconstructed PDSI in each cluster.

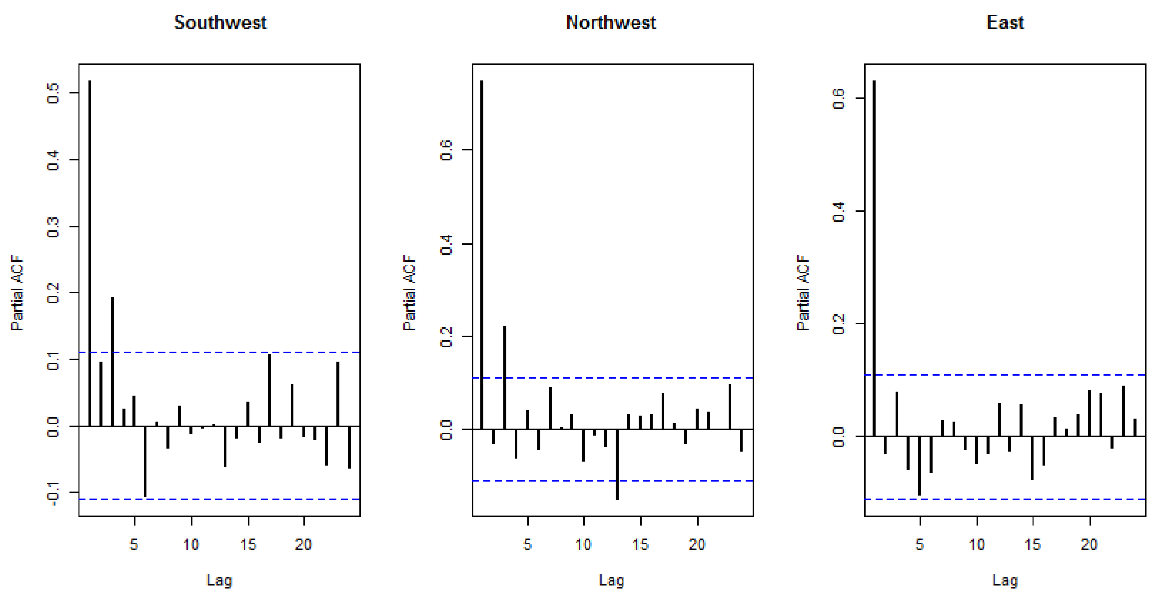


Figure 3-6: PACF of the tree-ring reconstructed PDSI in each cluster.

### *Climate variables*

Models that use climate variables as covariates are explored for developing a nonstationary risk model. These data are summarized in Table 3-2. We use high-resolution gridded datasets at Climate Research Unit (CRU) at University of East Anglia for monthly temperature, and summer and winter precipitation for the three clusters (Harris, Jones, Osborn, & Lister, 2014). All the gridded points within each cluster are averaged. We also used average monthly temperature data from instrumental records in Siberia. They are collected at three stations: Irkutsk (1882-2011), Minusinsk (1886- 2011), and Ulan Ude (1895-1989).

We also use the Arctic Oscillation (AO) index, which comes from two sources: the Joint Institute for the Study of the Atmosphere and Ocean (JISAO) and the National Oceanic and Atmospheric Administration (NOAA). The two records were scaled to be merged into one record (e.g. Kaheil and Lall, 2011)).

Finally, please note that though dry conditions of PDSI is negative, all the analyzed PDSI values below are presented in reversed values because the used R package, extReme (Gilleland & Katz, 2016), will capture the maximum values.

Table 3-2: List of data analyzed in this study

| | Types | Periods | Regions | Source |
|---|---|---|---|---|
| Tree-ring reconstructed PDSI data | 534 grid point reconstructions on a 2.5x2.5° grid | 1700 – 2013 | Southwest, Northwest, And East Mongolia | (Cook et al., 2010; National Centers for Environmental Information, n.d.) |
| Monthly temperature | High-resolution gridded climate datasets | 1901 - 2014 | Southwest, Northwest, And East Mongolia | (Climate Research Unit, n.d.)[3] |
| Monthly minimum temperature | High-resolution gridded climate datasets | 1901 – 2014 | Southwest, Northwest, And East Mongolia | (Climate Research Unit, n.d.) |
| Monthly temperature in Irkutsk, Siberia | Instrumental climate data | Sept. 1820 - June 2016 | - 52.27N, 104.32E. 469.0m (prob: 490m) - WMO station code: 30710 IRKUTSK | GHCN-M v3.3.0.20160703 |
| Monthly temperature in Ulan-UDE , Siberia | Instrumental climate data | Aug. 1886 - Dec. 1990 | - 51.83N, 107.60E, 515.0m (prob: 641m) - WMO station code: 30823 ULAN-UDE | GHCN-M v3.3.0.20160703 |
| Monthly temperature in Minusinsk, Siberia | Instrumental data | Jan. 1886 - June 2016. | - 53.70N, 91.70E, 254.0m (prob: 369m) - WMO station code: 29866 MINUSINSK | GHCN-M v3.3.0.20160703 |
| Summer and Winter precipitation | High-resolution gridded datasets | 1901 – 2014 | Southwest, Northwest, And East Mongolia | CRU |
| AO – Index | | 1903 - 2010 | | Joint Institute for the Study of the Atmosphere and Ocean (JISAO) and National Oceanic and Atmospheric Administration (NOAA). |

### 3.2.2. Methodology

Extreme Value Analysis (EVA) is utilized in this study. In EVA, the distribution of many variables can be stabilized so that their extreme values asymptotically follow specific distribution functions (Coles, 2001).

[3] Data is obtained from https://climexp.knmi.nl

There are two primary ways to analyze extreme data. The first approach, the so- called block maxima approach, reduces the data by taking maxima of long blocks data, such as annual maxima (Coles, 2001). The Generalized extreme value (GEV) distribution function is fitted to maxima of block data, as given by

$$\mathrm{G(z)} = \exp\left[-\left\{1+\varepsilon(\tfrac{z-\mu}{\sigma})\right\}_{+}^{-/\varepsilon}\ \right] \qquad (1)$$

where

$$y_{+} = \max\{y, 0\}, \sigma > 0, and -\infty < \mu, \varepsilon < \infty.$$

Equation (1) enclose three types of distribution function depending on the sign of the shape parameter ε The Fréchet distribution function is for $\varepsilon > 0$ while the upper bounded Weibull distribution function is for $\varepsilon < 0$ (Gilleland & Katz, n.d). The Gumbel type is obtained in the limit as $\varepsilon \to 0$, which results in

$$\mathrm{G(z)} = \exp\left[-exp\left[-\left\{\frac{z-\mu}{\sigma}\right\}\right]\right], -\infty < z < \infty$$

The second approach, the so-called threshold excess approach, is to analyze excesses over a high threshold (Coles, 2001). The generalized Pareto distribution (GPD) has a theoretical justification for fitting to the threshold excess approach (Gilleland & Katz, 2016), as given by

$$\mathrm{H(x)} = 1 - \left[1+\varepsilon\left(\frac{x-\mu}{\sigma_{\mu}}\right)\right]_{+}^{-1/\varepsilon}$$

where μ is a high threshold, x> μ, scale parameter $\sigma_{\mu}$>0 and shape parameter $-\infty < \varepsilon < \infty$. The shape parameter $\varepsilon$ determines three types of distribution functions: heavy-tailed Pareto when $\varepsilon$>0, upper bounded Beta when $\varepsilon$<0, and the exponential is obtained by taking the limit as $\varepsilon \to 0$, which gives

$$\mathrm{H(x)} = 1 - e^{-(x-\mu)/\sigma}$$

The extreme value models can be applied in the presence of temporal dependence (Coles, 2001), as given below:

$$\mathrm{Zt}\sim \mathrm{GEV}\ (\mu(t), \sigma(t), \varepsilon(t))$$

Where

$$\mu(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + .. + \alpha_n t^n$$

$$\sigma(t) = \exp(\beta_0 + \beta_1 t + .. + \beta_n t^n)$$

$$\varepsilon(t) = \begin{cases} \varepsilon_0, & t \le t_0 \\ \varepsilon_1, & t > t_0 \end{cases}$$

By examining the times series of the PDSI values and winter minimum temperature, we can enhance the understanding of how return periods of droughts, extreme cold weather have changed over time. The best GEV and GPD models are selected based on Maximum Likelihood Estimation (MLE) and Bayesian Information Criterion (BIC) (Katz, 2013). Also, it is examined in diagnostic plots whether the best GEV and GPD models are reasonably fit to distributions or not.

## 3.3 Results and Discussion

### 3.3.1 Return Periods of Droughts Using Tree-ring Reconstructed PDSI data

In this section, to find the best model to predict a drought condition with the extended time, GEV and GP distributions are fit to the tree-ring reconstructed PDSI values for approximately 300 years, from 1700 to 2013. The procedure is implemented as follows:

1. Fit GEV distributions to the tree-ring reconstructed PDSI values, allowing for non-stationarity by making μ, σ, and/ or ε a function of time.
2. Fit GEV distributions to the tree-ring reconstructed PDSI values using climate variables (AO index, summer precipitation, snow, and minimum temperatures).
3. Evaluate models based on BIC.
4. Using the best GEV model, return periods are estimated.
5. The above procedure is repeated for GPDs fit to the tree-ring reconstructed PDSI values.

#### *Fitting GEV to the Tree-Ring Reconstructed PDSI for Return Period Estimation*

We construct two types of models: (1) stationary and nonstationary extreme value models, and (2) nonstationary models using climatic variables as covariates. First, we consider polynomial models in time of the order of 0 to 2 for both the location and scale parameters of the GEV distribution, resulting in seven models to be tested, including the stationary model, for each region. In addition, autoregressive (AR) models are examined. The models are evaluated based on the BIC (Table 3-3). The best GEV models and its maximum likelihood estimates (MLE) with 95% confidence intervals are as follows (Table 3-3,Table 3-4):

- Southwest: the model with a constant in the location parameter and temporally linear model in the scale parameter:

  $$\mu = -0.42;\ \sigma = 0.95 + 0.002t;\ \varepsilon = -0.23.\ \mathrm{BIC} = 1045.$$

  $$\mu = -0.39 + 0.36PDSI_{t-3};\ \sigma = 1.19\ ;\ \varepsilon = -0.29.\ \mathrm{BIC} = 1005.$$

- Northwest: the model with a constant both in the location and scale parameters:

  $$\mu = -0.67;\ \sigma = 1.68;\ \varepsilon = -0.25;\ \mathrm{BIC} = 1241.$$

  $$\mu = -0.57 + 0.50PDSI_{t-3};\ \sigma = 1.47\ ;\ \varepsilon = -0.27.\ \mathrm{BIC} = 1146.$$

- East: the model with a constant both in the location and scale parameters:

  $$\mu = -0.93;\ \sigma = 1.65;\ \varepsilon = -0.31;\ \mathrm{BIC} = 1212.$$

  $$\mu = -0.55 + 0.62PDSI_{t-3};\ \sigma = 1.25\ ;\ \varepsilon = -0.22.\ \mathrm{BIC} = 1064.$$

Table 3-3: BIC values for stationary and non-stationary GEV models fitted to the tree-ring reconstructed PDSI values.

| BIC | Stationary model | Non-stationary model | | | | | | AR model |
|---|---|---|---|---|---|---|---|---|
| | | L=1,S=0 | L=0,S=1 | L=1,S=1 | L=2,S=1 | L=1,S=2 | L=2,S=2 | |
| Southwest | 1049 | 1053 | **<u>1045</u>** | 1048 | 1050 | 1053 | 1056 | 1005 AR(3) |
| Northwest | **<u>1241</u>** | 1246 | 1246 | 1252 | 1242 | 1252 | 1248 | 1146 AR(3) |
| East | **<u>1212</u>** | 1248 | 1218 | 1216 | 1217 | 1222 | 1222 | 1064 AR(1) |

*Note: L stands for the location parameters, S stands for the scale parameters. 0 means a constant in the parameter, 1 is temporally linear, and 2 is temporally quadratic for each parameter.*

Table 3-4: 95% Confidence intervals of parameters based on the normal approximation for each region.

| | 95% lower CI | Estimate | 95% upper CI |
|---|---|---|---|
| Southwest | | | |
| Location ($\alpha_0$) | -0.56 | -0.42 | -0.28 |
| Scale ($\beta_0$) | 0.75 | 0.95 | 1.15 |
| Scale ($\beta_1$) | 0.001 | 0.002 | 0.003 |
| Shape ($\varepsilon$) | -0.29 | -0.23 | -0.17 |
| Northwest | | | |
| Location($\alpha_0$) | -0.87 | -0.67 | -0.46 |
| Scale ($\beta_0$) | 1.53 | 1.68 | 1.82 |
| Shape ($\varepsilon$) | -0.32 | -0.25 | -0.18 |
| East | | | |
| Location($\alpha_0$) | -0.93 | -0.73 | -0.52 |
| Scale ($\beta_0$) | 1.51 | 1.65 | 1.80 |
| Shape ($\varepsilon$) | -0.38 | -0.31 | -0.24 |

Table 3-5: 95% Confidence intervals of parameters based on the normal approximation for each region

| | 95% lower CI | Estimate | 95% upper CI |
|---|---|---|---|
| Southwest | | | |
| Location ($\alpha_0$) | -0.54 | -0.39 | -0.25 |
| Location($\alpha_1$) | 0.26 | 0.36 | 0.46 |
| Scale ($\beta_0$) | 1.10 | 1.19 | 1.29 |
| Shape ($\varepsilon$) | -0.35 | -0.30 | -0.24 |
| Northwest | | | |
| Location($\alpha_0$) | -0.75 | -0.57 | -0.39 |
| Location($\alpha_1$) | 0.40 | 0.50 | 0.59 |
| Scale ($\beta_0$) | 1.34 | 1.47 | 1.59 |
| Shape ($\varepsilon$) | -0.34 | -0.27 | -0.20 |
| East | | | |
| Location($\alpha_0$) | -0.70 | -0.55 | -0.40 |
| Location($\alpha_1$) | 0.54 | 0.62 | 0.71 |
| Scale ($\beta_0$) | 1.15 | 1.25 | 1.35 |
| Shape ($\varepsilon$) | -0.27 | -0.22 | -0.17 |

These results suggest that in the long run, a stationary model for PDSI in Mongolia may be appropriate. Only the Southwest has nonstationarity in the scale parameter, and this could be a real feature or an artifact of the non-constant reconstruction variance from the tree ring reconstruction algorithm.

Next, we estimate parameters of the GEV distribution functions fit to the PDSI values by including other climate variables such as AO index, summer precipitation, snow, and minimum temperatures as covariates from 1903 to 2010. Summer precipitation is a mean of May to August of a previous year, while snow is mean of values from November of a previous year to February of the year. The minimum temperature is a minimum value from November of a previous year to October of the year. The GEV models with the lowest BIC for each cluster and MLEs with the 95% confidence intervals are as follows (Table 3-5 and Table 3-6):

- Southwest: *Precipitation* data as a linear covariate in the location parameter:

  $$\mu = 3.63 - 0.14 Precipitation;\ \sigma = 1.12;\ \varepsilon = -0.21. (\mathrm{BIC} = 358).$$

- Northwest: *Precipitation* data as a linear covariate in the location parameter and *snow* data as a linear covariate in the scale parameter.

  $$\mu = 6.25 - 0.15 Precipitation;\ \sigma = 2.38 - 0.31 snow; \varepsilon = -0.07. (\mathrm{BIC} = 380).$$

- East: *Precipitation* data as a linear covariate in the location parameter.

  $$\mu = 5.09 - 0.13 Precipitation;\ \sigma = 1.48;\ \varepsilon = -0.24. (\mathrm{BIC} = 380).$$

In the GEV models, climate variables (precipitation and snow) are important covariates for the extreme values of the PDSI values and improve the model performance (Table 3-3). These climate variables have no inter -year dependence that is significant based on ARIMA, and hence there is no memory in these variables and the best model is stationary model. Consequently, no near term forecast is feasible.

Table 3-6: BIC values in estimated GEV models fitted to the PDSI values using the climate variables from 1903 to 2010.

| | | Scale | | | | |
|---|---|---|---|---|---|---|
| **Southwest** | | | | | | |
| | | Constant | AO | Snow | Tmin | Precip |
| Location | Constant | 392 | 397 | 397 | 394 | 391 |
| | Linear trend | 390 | 393 | 393 | 394 | 393 |
| | Quadratic trend | 387 | 390 | 391 | 387 | 390 |
| | AO | 397 | 401 | 401 | 397 | 393 |
| | Snow | 397 | 401 | 401 | 398 | 395 |
| | Tmin | 396 | 401 | 401 | 396 | 395 |
| | Precip | **358** | 361 | 362 | 362 | 362 |
| **Northwest** | | | | | | |
| | | Constant | AO | Snow | Tmin | Precip |
| Location | Constant | 430 | 434 | 433 | 433 | 432 |
| | Linear trend | 433 | 437 | 437 | 437 | 436 |
| | Quadratic trend | 427 | 431 | 431 | 429 | 425 |
| | AO | 434 | 438 | 437 | 437 | 437 |
| | Snow | 434 | 438 | 437 | 437 | 437 |
| | Tmin | 433 | 437 | 437 | 436 | 436 |
| | Precip | 384 | 388 | **380** | 387 | 387 |
| **East** | | | | | | |
| | | Constant | AO | Snow | Tmin | Precip |
| Location | Constant | 439 | 437 | 444 | 443 | 440 |
| | Linear trend | 441 | 446 | 445 | 446 | 445 |
| | Quadratic trend | 440 | 445 | 445 | 445 | 443 |
| | AO | 444 | 448 | 448 | 448 | 445 |
| | Snow | 439 | 444 | 442 | 443 | 441 |
| | Tmin | 444 | 448 | 448 | 448 | 444 |
| | Precip | **416** | 418 | 418 | 420 | 419 |

Table 3-7: 95% Confidence intervals of parameters, using other climate variables based on the normal approximation

| | 95% lower CI | Estimates | 95% Upper CI |
|---|---|---|---|
| Southwest | | | |
| Location ($\alpha_0$) | 2.49 | 3.63 | 4.77 |
| Location ($\beta_1$) | -0.18 | -0.14 | -0.11 |
| Scale ($\beta_0$) | 0.96 | 1.12 | 1.28 |
| Shape($\varepsilon$) | -0.33 | -0.21 | -0.10 |
| Northwest | | | |
| Location ($\alpha_0$) | 4.84 | 6.25 | 7.67 |
| Location ($\alpha_1$) | -0.17 | -0.15 | -0.12 |
| Scale ($\beta_0$) | 1.60 | 2.38 | 3.17 |
| Scale ($\beta_1$) | -0.48 | -0.31 | -0.14 |
| Shape ($\varepsilon$) | -0.20 | -0.07 | 0.06 |
| East | | | |
| Location ($\alpha_0$) | 3.01 | 5.09 | 7.17 |
| Location ($\beta_1$) | -0.17 | -0.13 | -0.08 |
| Scale ($\beta_0$) | 1.26 | 1.48 | 1.71 |
| Shape ($\varepsilon$) | -0.39 | -0.24 | -0.10 |

The time series of effective return periods of 100-year events for the GEV distribution functions fitted to the PDSI using the climate variables are shown in each region (Figure 3-7) from 1903 to 2010. This shows that variabilities of return periods of 100-year events of the PDSI values become larger over time in all the regions. Before 1940, the variabilities are small possibly because the instrumental data records began in 1940's. Even after 1940's, it also shows that the magnitude of 100-year events has increased in the last half of the data series. A PDSI value of 3 used to be a 100 year event around 1920. Yet, around the beginning of the 21st century, it has increased to be between 4 and 5. However, considerable inter-annual and decadal variability is evident.

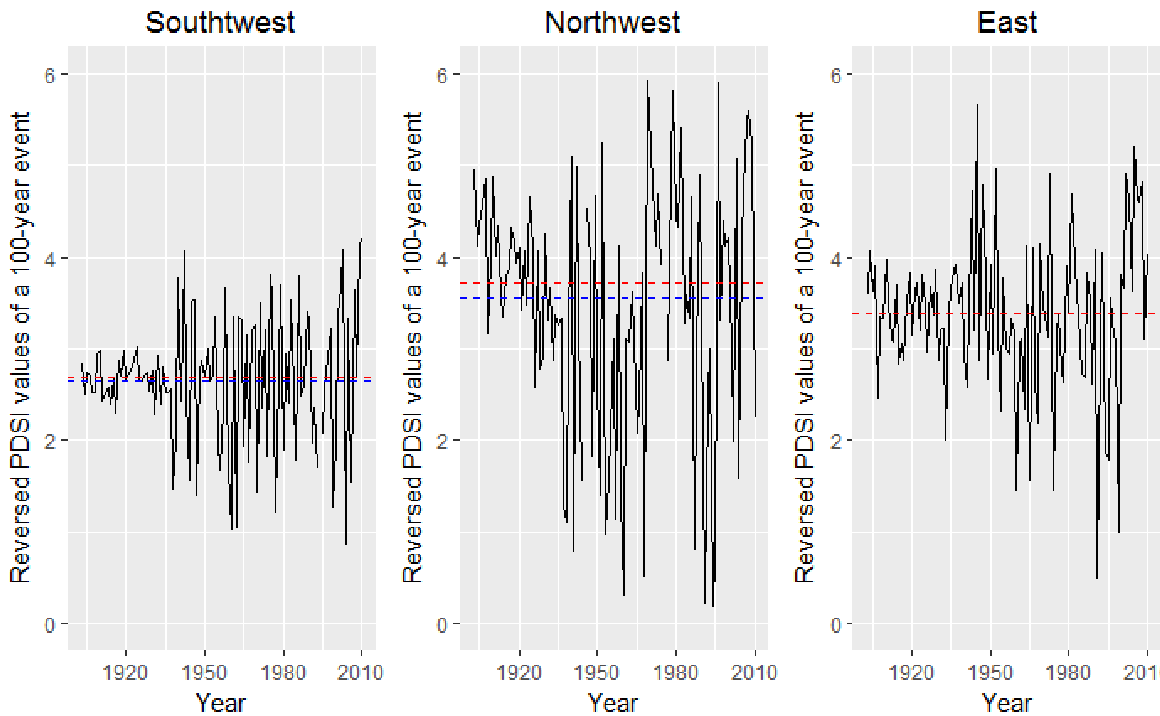


Figure 3-7: Estimated effective return levels of a 100-years event from the GEV distribution function fitted the PDSI values in the Southwest over 1903 to 2010 with precipitation data as a linear covariate in the location parameter. The blue horizontal line is the mean of the effective return levels while the red one is its median. Please note that the vertical axis is shown by the reversed values of PDSI values, meaning that a positive value is a drought condition.

The relationship between significant climate covariates and reversed reconstructed PDSI values based on the best GEV models for each return period of 10, 50, and 100 years events are shown in Figure 3-8, Figure 3-9, and Figure 3-10. This shows that less precipitation leads to higher reversed reconstructed PDSI values, meaning more likelihood of droughts. Consequently, with this model, future projections of precipitation could be helpful to predict drought severity and frequency.

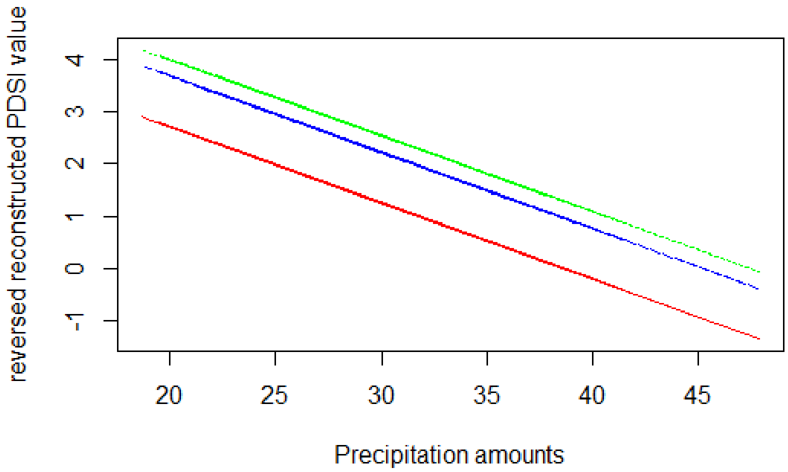


Figure 3-8: Relationship between precipitation and reversed reconstructed PDSI values in the Southwest based on the best GEV model. Since the PDSI values are reversed, the positive values mean drought conditions. The red, blue and green lines are 10 year, 50 year, and 100 year events.

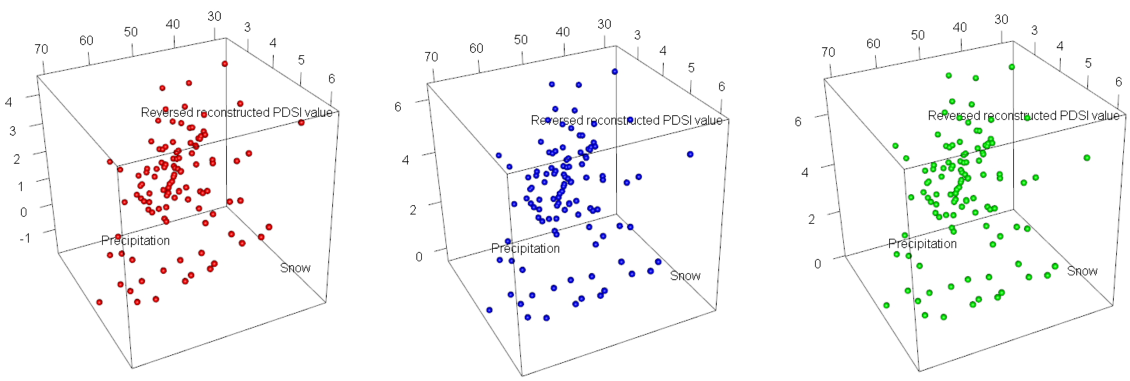


Figure 3-9: Relationship between precipitation, snow and reversed reconstructed PDSI values in the Northwest based on the best GEV model. Since the PDSI values are reversed, the positive values mean drought conditions. The x axis is precipitation, the y-axis is snow, and the z-axis is reversed reconstructed PDSI values. The right cube is for 10-year events, the central is for 50-year events, and the right is for 100-year events.

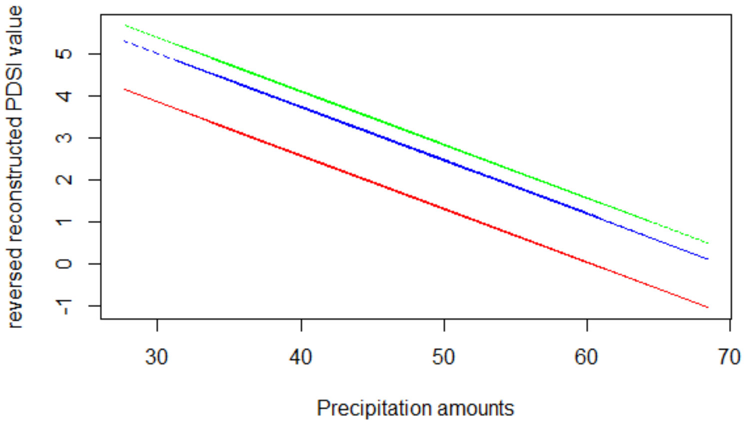


Figure 3-10: Relationship between precipitation and reversed reconstructed PDSI values in the East based on the best GEV model. Since the PDSI values are reversed, the positive values mean drought conditions. The red, blue and green lines are 10 year, 50 year, and 100 year events.

### *Fitting GPD to the Tree-Ring Reconstructed PDSI for the Return Periods Estimation*

To fit a GPD, a threshold needs to be selected. Figure 3-11 repeatedly fits the GPD to the data for a series of threshold choices along with uncertainty (Gilleland & Katz, 2016). Figure 3-12 plots the mean excess values for a sequence of threshold choices with some variability information (Gilleland & Katz, 2016). As discussed in Gilleland & Katz (2016), choice of a threshold is subjective. Because a good choice of the threshold is near the inflection point of the right tail of the distribution, the value of 1.0 is selected as a threshold. This selection of 1 seems to yield estimates that will not change much as the threshold increases further from Figure 3-12. Also, Gilleland & Katz (2016) suggests selecting a threshold whereby the graph is linear within uncertainty bounds in the plot of the mean excess values. Following this, the threshold value of 1 is a reasonable choice in Figure 3-11. Furthermore, if I use this value for the threshold, the exceedance percentile of the threshold (a ratio of the number of exceedance to the number of total data) is 0.210 in the Southwest and 0.26 for both the northwest and east. Therefore, it is reasonable to use a threshold of 1.0.

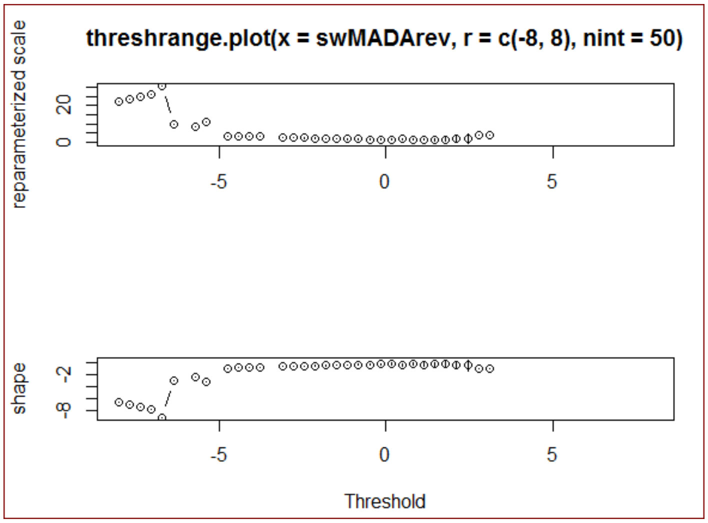


Figure 3-11: Threshold Range Plot (1)

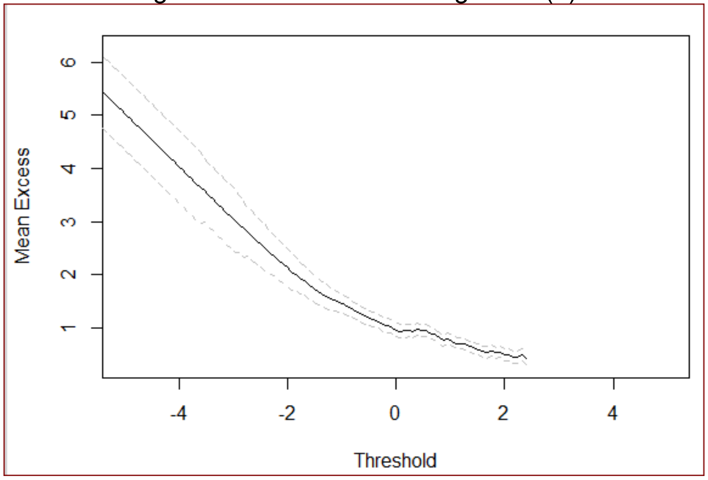


Figure 3-12: Threshold Range Plot (2)

GPDs are fit to the tree-ring reconstructed PDSI values from 1700 C.E. as both stationary and non-stationary models (Figure 3-8). The model of stationarity is best in terms of BIC for all clusters.

Table 3-8: BIC for non-stationary models in the scale parameters of GPD models fitted to the tree-ring reconstructed PDSI from 1700 for each clusters.

| BIC | Constant | Linear in time | Quadratic in time |
|---|---|---|---|
| Southwest | **97.00** | 100.30 | 104.40 |
| Northwest | **184.69** | 188.37 | 188.41 |
| East | **143.49** | 145.01 | 148.25 |

The likelihood ratio test shows the same conclusion. The likelihood ratio between temporal linear and stationary models shows that the p-value is 0.24. The likelihood ratio test between temporal quadratic and stationarity model shows 0.49 of p-values. Both results show that the subset models do not improve significantly.  These results confirm that where the interest is in extreme dry? PDSI values a stationary model is appropriate.

Being similar to the GEV cases, we analyze the other climate variables after 1903. The results are shown in Table 3-9. The results show that the best model of GPD is the one with a constant in the scale parameters in terms of BIC for all clusters. MLEs estimated by the best GPD models are shown in Table 3-10. The table shows that for catastrophic droughts, climate variables are not a significant covariate, although the differences in BIC values in the Southwest and Northwest between the ones with constants and with AO index are small. The estimated effective return periods based on these best GPD models are listed in Table 3-11.

Table 3-9: BIC values for different GPD models fitted to the tree-ring reconstructed PDSI values from 1903 with climate variables for all clusters

| Predictors in the scale parameters | Constant | AO | Snow | Tmin | Precip |
|---|---|---|---|---|---|
| Northwest | **30.21** | 31.37 | 32.16 | 32.20 | 31.96 |
| Southwest | **50.38** | 50.82 | 53.00 | 52.09 | 52.76 |
| East | **65.49** | 68.84 | 68.62 | 68.86 | 67.80 |

Table 3-10: 95% Confidence intervals of parameters, using other climate variables based on the normal approximation

| | 95% lower CI | Estimate | 95% upper CI |
|---|---|---|---|
| Southwest | | | |
| Scale ($\beta_0$) | 0.33 | 0.78 | 1.24 |
| Shape ($\varepsilon$) | -0.64 | -0.20 | 0.22 |
| Northwest | | | |
| Scale ($\beta_0$) | 0.78 | 2.02 | 3.25 |
| Shape($\varepsilon$) | -1.01 | -0.53 | -0.05 |
| East | | | |
| Scale($\beta_0$) | 0.85 | 1.88 | 2.91 |
| Shape($\varepsilon$) | -1.13 | -0.65 | -0.18 |

Table 3-11: Effective return levels of 10, 50, and 100 year events of the PDSI values, based on the best GPD models. (Actual PDSI values are negative of these values).

| | 10 year event | 50 year event | 100 year event |
|---|---|---|---|
| Southwest | 3.82 | 4.08 | 4.17 |
| Northwest | 4.68 | 4.75 | 4.76 |
| East | 3.85 | 3.87 | 3.87 |

## *Results Based on GEV and GPD Models*

In this section, we fitted the GEV and GPD distribution functions to the PDSI values. Results are the following:

- All the results show that the PDSI values will follow the distributions with $\varepsilon<0$, namely the Weibull distribution for the GEV models and the upper-bounded Beta distribution for the GPD models.

- For the Southwest, the non-stationary models performed better if we look at GEV without a threshold. However, with a threshold of 1 for the GPDs, the stationary models perform better than the non-stationary models, which indicate that all trends in reconstructed PDSI values are influenced by small events, not by extreme events; i.e. extreme events are stationary. For both the Northwest and East, stationary models performed better for both the GEV and GPD models.
- Compared to the models with constants in the parameters, the GEV model with the climate variables are better in terms of the BIC value. Therefore, establishing a relationship between drought conditions and climate variables, particularly precipitation and snow, is useful in understanding the dynamics that determine dry conditions. However, compared to the models with constants in the scale parameters, the GPD models with the climate variables don't lead to the improvement of the model performance. Hence, the climate variables are not so useful for understanding the dry conditions.
- In terms of BIC, the models of a GPD fitted to tree-ring reconstructed PDSI values show better performance than the GEV models.
- Because of the third point, the effective return periods based on the GEV models change with the climate variables. In contrast, the effective return levels based on the GPD models are constant: for example, a 100-year event is the PDSI value of -4.17 for the Southwest, -4.76 for the Northwest, and -3.87 for the East.

### 3.3.2. Simulating Annual Minimum Temperature in Mongolia Using Siberia Data

The data of Mongolia winter temperature is limited before 1901. Thus, we attempt to estimate the Mongolia data from instrumental Siberia data, which cover longer time periods since the early 19$^{th}$ century. The procedure is implemented in the following way:

1. Conduct correlation analysis between Siberia and Mongolia data to select which station data are informative for temperature in Mongolia.
2. Impute missing data of instrumental data in Siberia
3. Fit a GEV and GPD to the winter minimum temperature in Mongolia with the Siberia data
4. Simulate winter minimum temperature of Mongolia from Siberia data based on the best GEV model.

5. Calculate effective return periods of 10, 50, and 100 years from the simulated winter minimum temperature of Mongolia.

First, correlation analysis is conducted to see which station data in Siberia is useful for Mongolia data. Temperature data in both Mongolia and Siberia is monthly data. Thus, to remove the seasonality, we use minimum temperature and average temperature during the winter time (October to April). Data are taken for the common periods when all the points have data (i.e. between 1901 – 1990). Irkutsk data alone is used since it alone shows significant correlations (Results of Pearson and Spearman correlation coefficients and scatter plots are shown respectively in in Figure B-1, Figure B-2, and Table B-1). We also check the ACF of residuals between data from Irkutsk, Siberia and winter average temperature of each cluster. Figure 3-13 shows there is no significant ACF structures between these data.

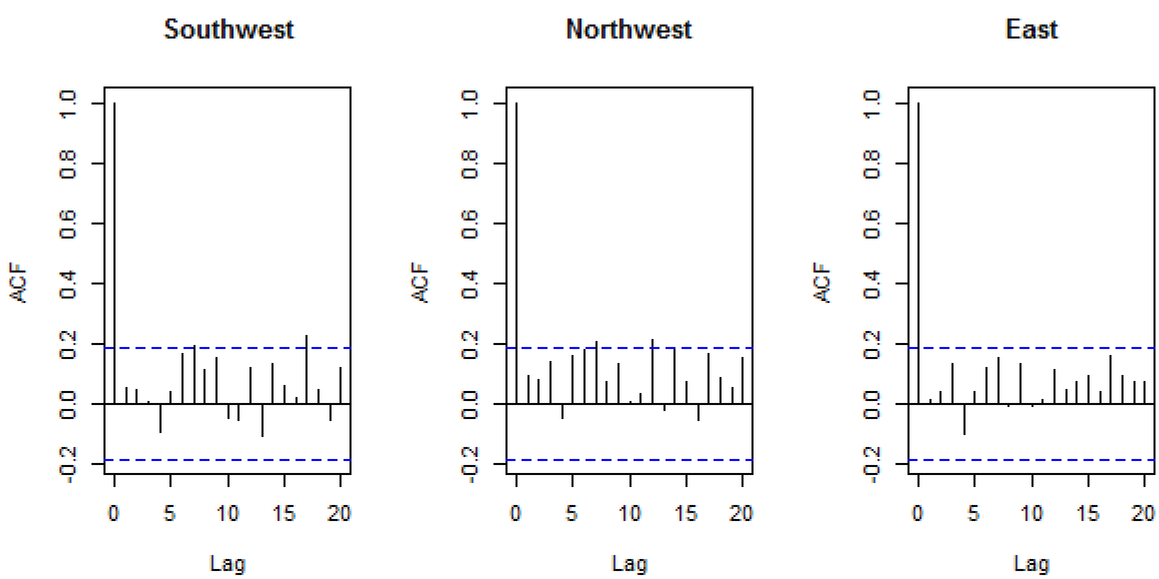


Figure 3-13: ACF of residuals between data from Irkutsk Siberia and the winter average temperature of each cluster.

Next, we check the structures of missing data of instrumental data from Irkutsk, Siberia. Some of the years have missing data in an entire year. We impute Irkutsk's data with pattern matching methods, which is equivalent to k-nearest neighbors, by Gibbs sampling using predictive mean matching method (Buuren & Groothuis-Oudshoorn, 2011).

Using winter minimum temperature from the Irkutsk data in Siberia (*$Tmin_{Irkutsk}$*) as a covariate, we fit the Mongolia winter minimum temperature (*$Tmin_{mongolia}$*) based on the GEV and GPD models.

### *Fitting GEV to the Winter Minimum Temperature in Mongolia*

The results for GEV models based on BIC are shown in Table 3-12. Models with Siberia data both in the location and scale parameter are the lowest BIC for the Southwest and Northwest. For East, the one with Siberia data in the location parameter and constant in the scale parameter shows the lowest BIC (Table 3-12). The best models for each region are in Table 3-13 and in the following:

$$\mathrm{H}(Tmin_{mongolia}) = 1 - \left[1 + \varepsilon\left(\frac{Tmin_{mongolia} - \mu}{\sigma_{\mu}}\right)\right]_{+}^{-1/\varepsilon}$$

$$\mathrm{Zt} \sim \mathrm{GEV}\ (\mu(\mathrm{t}), \sigma(\mathrm{t}), \varepsilon(\mathrm{t}))$$

where

$$\mu(Tmin_{Irkutsk}) = \beta_0 + \beta_1 * Tmin_{Irkutsk}$$

$$\sigma(Tmin_{Irkutsk}) = \exp(\beta_3 + \beta_4 * Tmin_{Irkutsk})$$

$$\varepsilon(\mathrm{t}) = \begin{cases} \varepsilon_0, & t \le t_0 \\ \varepsilon_1, & t > t_0 \end{cases}$$

Southwest: $\mu = 11.80 + 0.39 Tmin_{Irkutsk};\ \sigma = 1.90;\ \varepsilon = -0.25.$

Northwest: $\mu = 12.67 + 0.52 Tmin_{Irkutsk};\ \sigma = exp(0.35 + 0.06 Tmin_{Irkutsk});\ \varepsilon = -0.18.$

East: $\mu = 10.20 + 0.48 Tmin_{Irkutsk};\ \sigma = 1.40;\ \varepsilon = -0.38.$

Table 3-12: BIC values for GEV models using Irkutsk data for 3 clusters

| | Stationary | Location= $Tmin_{Irkutsk}$, scale=1 | Location=1, scale= $Tmin_{Irkutsk}$ | Location=$Tmin_{Irkutsk}$, scale= $Tmin_{Irkutsk}$ |
|---|---|---|---|---|
| Southwest | 527.40 | **494.45** | 528.98 | 497.40 |
| Northwest | 537.04 | 467.87 | 532.89 | **467.74** |
| East | 495.48 | **403.36** | 846.02 | 901.64 |

Table 3-13: Estimated parameters based on the best GEV model fitted to the winter minimum temperature in Southwest using Irkutsk data.

| | Estimate | Standard Error Estimates |
|---|---|---|
| Southwest | | |
| Location ($\alpha_0$) | 11.82 | 1.22 |
| Location ($\alpha_1$) | 0.39 | 0.06 |
| Scale ($\beta_0$) | 1.90 | 0.14 |
| Shape ($\varepsilon$) | -0.25 | 0.06 |
| Northwest | | |
| Location ($\alpha_0$) | 12.67 | 1.00 |
| Location ($\alpha_1$) | 0.52 | 0.05 |
| Scale ($\beta_0$) | 0.35 | 0.66 |
| Scale ($\beta_1$) | 0.06 | 0.03 |
| Shape | -0.18 | 0.06 |
| East | | |
| Location ($\alpha_0$) | 10.20 | 0.80 |
| Location ($\alpha_1$) | 0.48 | 0.04 |
| Scale ($\beta_0$) | 1.40 | 0.10 |
| Shape ($\varepsilon$) | -0.38 | 0.05 |

### *Fitting GPD to the Winter Minimum Temperature in Mongolia*

For GPD, we select 20 (-20 degrees in reality) as a threshold. In this case, the one with the Irkutsk's data in the scale parameter has the lowest BICs for all clusters as Table 3-14 shows.

Table 3-14: BIC values of GPD models using Irkutsk data for 3 clusters

| | Stationary | Scale = $Tmin_{Irkutsk}$ |
|---|---|---|
| Southwest | 242.00 | **236.00** |
| Northwest | 503.92 | **479.89** |
| East | 203.52 | **180.15** |

Table 3-15: Estimated parameters based on the best GPD model fitted to the winter minimum temperature in Southwest using Irkutsk data.

| | Estimate | Standard Error Estimates |
|---|---|---|
| Southwest | | |
| Scale ($\sigma_0$) | -4.18 | 1.60 |
| Scale ($\sigma_1$) | 0.34 | 0.09 |
| Shape | -0.54 | 0.13 |
| Northwest | | |
| Scale($\beta_3$) | 2.30 | 2e-08 |
| Scale ($\beta_4$) | 0.35 | 2e-08 |
| Shape | -1.15 | 2e-08 |
| East | | |
| Scale | -1.63 | 2e-08 |
| Scale ($\beta_4$) | 0.26 | 2e-08 |
| Shape | -1.06 | 2e-08 |

### *Results based on GEV and GPD models*

In this section, we fitted the GEV and GPD distribution functions to the winter minimum temperature in Mongolia. The results are as follows:

- All the results show that the winter minimum temperature will follow the distributions with ε<0, namely the Weibull distribution for GEV and the upper-bounded Beta distribution.
- Based on BIC, GPD models show better performance in both Southwest and East regions, while the GED models show better performance in Northwest.

### 3.3.3. Return Periods of the Winter Minimum Temperature in Mongolia Simulated from Siberia Data

Next, we simulate the Mongolia winter minimum temperature based on data in Irkutsk Siberia for 197 years using the parameters estimated by the best GEV model. We use the GEV model because the winter minimum temperature data is a single extreme value and that the GEV model is suitable for maxima and minima of block data. Then, using this simulated Mongolia winter minimum temperatures, we estimate the 90% confidence intervals of return levels of 10, 50 and 100 year events for each cluster (Figure 3-14, Figure 3-15, Figure 3-16). The median of 100 year return levels are -26.08, -27.99, and -25.31 Celsius degrees for the Southwest, Northwest, and East.

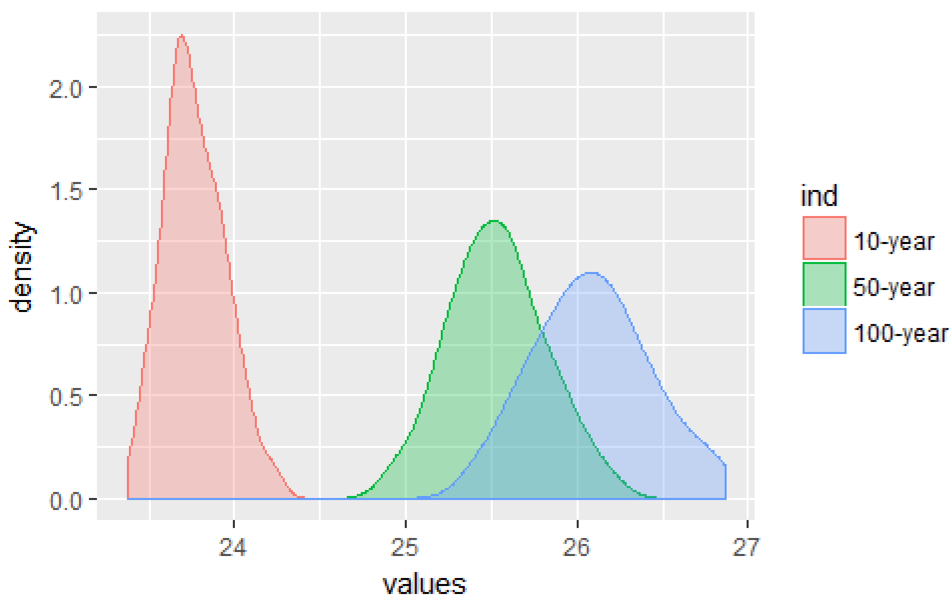


Figure 3-14: Density plots of 10, 50, and 100-year return levels of the winter minimum temperatures in the Southwest of Mongolia with 90% confidence intervals. The data is simulated 100 times from the Siberia data.

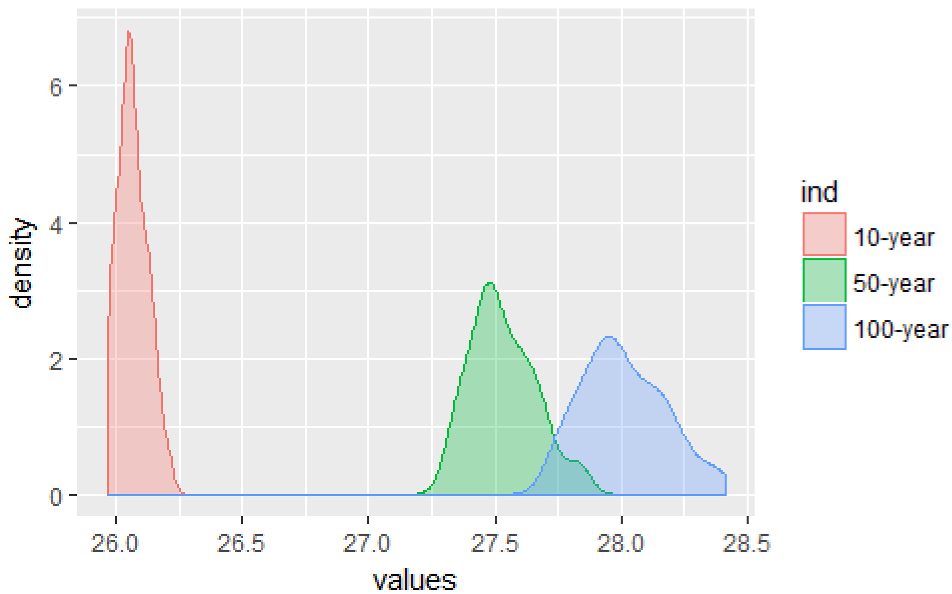


Figure 3-15: Density plots of 10, 50, and 100-year return levels of the winter minimum temperatures in the Northwest of Mongolia with 90% confidence intervals. The data is simulated 100 times from the Siberia data.

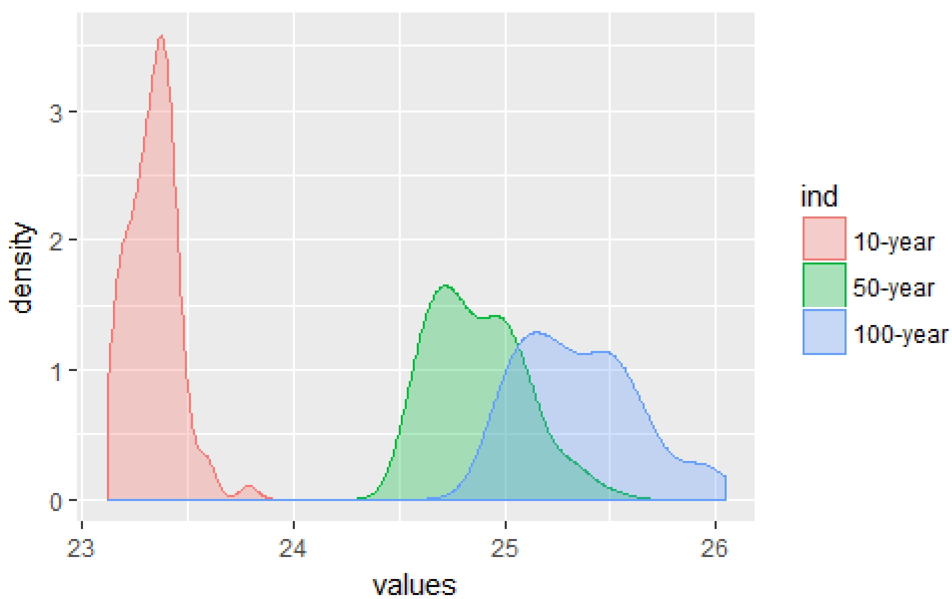


Figure 3-16: Density plots of 10, 50, and 100-year return levels of the winter minimum temperatures in the East of Mongolia with 90% confidence intervals. The data is simulated 100 times from the Siberia data.

## 3.4. Conclusions

Meteorological data in Mongolia is limited; its quality is not desirable and this data did not exist before the early 20$^{th}$ century. Therefore, utilizing longer time scale of paleoclimate proxy data and meteorological data from neighboring Siberia, this study attempts to improve risk estimation for dzud in Mongolia. Specifically, based on extreme value theory, the study derives fitted distributions for the extreme climate events. The study also improves the estimation of return periods of drought conditions and winter temperature, using tree-ring reconstructed self-calibrated PDSI, climate variables in Mongolia and Siberia.

Looking at the GEV models without a threshold shows that there is a non-stationarity trend in tree-ring reconstructed PDSI data in the Southwest, while there is a stationarity trend in PDSI in both the Northwest and East. However, the threshold approach indicates that extreme events in reconstructed PDSI values are stationary.

The study estimated the extreme distributions of drought and winter minimum temperatures in Mongolia. The PDSI values follow the distributions with $\varepsilon<0$, namely the Weibull distribution for the GEV models and the upper-bounded Beta distribution for the GPD models. Also, the results of the study show that the winter minimum temperature follow the distributions with $\varepsilon<0$, namely the Weibull distribution for GEV and the upper-bounded Beta distribution. These estimated distributions can be used to improve the risk calculations for livestock index insurance in Mongolia.

Based on the results of our GEV fitted to the PDSI values, we show that climate variables, such as precipitation and snow, are important covariates for the extreme values of the reconstructed PDSI values. However, based on the results of the GPD model fitted to the PDSI values, climate variables are not significant covariates for catastrophic drought events.

Based on the GEV, the return levels of drought conditions are changing over time and its variabilities are increasing for all the regions. Yet, based on GPD, the return levels of drought conditions are constant: for example, the actual values of the PDSI for the 100-year events are: -4.17 for the Southwest, -4.76 for the Northwest, and -3.87 for the East. The median of 100-year return levels of the winter minimum temperature in Mongolia is -26.08 Celsius degrees for the Southwest, -27.99 Celsius degrees for the Northwest, and -25.31 Celsius degrees for the East.

This study improves the return period estimation of droughts and winter minimum temperature. Summer drought and winter temperature are important predictors for livestock mortality since they explain 48.4% of the total variability in the mortality data, along with summer precipitation and summer potential evapotranspiration (Rao et al., 2015). Therefore, this long-term estimation of return periods of these significant predictors can be used to improve risk analysis of high livestock mortality in order to prepare for the winter catastrophes through early warning systems and index insurance. Particularly, the estimation of extreme value distributions and return levels has the potential to improve the livestock index insurance, which is implemented in Mongolia by the Government of Mongolia with the help of the World Bank (Mahul et al., 2015). Furthermore, the results of this study increase the understanding of how extreme climatic events in arid regions, which are sensitive to anthropogenic climate change, is changing. If we consider recent trends in Eurasia's sever winters influenced by the Arctic ice-melting (Mori, Watanabe, Shiogama, Inoue, & Kimoto, 2014), the urgent needs to improve resilience of the society to this winter disaster is even more unequivocal.

# CHAPTER 4. CRITICAL INFRASTRUCTURE INTERDEPENDENCE IN NEW YORK CITY DURING HURRICANE SANDY


## Abstract

**Purpose** – This study is to investigate the impact of Hurricane Sandy from the perspective of interdependence among different sectors of critical infrastructure in New York City and to assess the interconnected nature of risks posed by such a hurricane.

**Design/methodology/approach** – This study uses indirect damages of each sector to estimate the degree of functional interdependence among the sectors. The study examines the impact of the hurricane on different critical infrastructures by combining hazard maps of actual inundation areas with maps of critical infrastructure. The direct damages of each sector are calculated from the inundation areas in the flood map. The indirect damages are estimated by considering the areas that were not inundated but affected by Sandy through the interconnected infrastructure.

**Findings** – The electricity sector was the key sector to propagate risks to other sectors. The examination of new initiatives to increase the resilience of critical infrastructures in New York City after Sandy reveals that these initiatives focus primarily on building hard infrastructures to decrease direct damages. They understate the importance of interdependent risk across sectors. Future disaster risk reduction strategies must address interdependent infrastructures to reduce indirect damages.

**Originality/value** – This paper estimates the direct and indirect damages caused by Hurricane Sandy in each critical infrastructure sector, using GIS mapping techniques. The methodology enables a quick assessment of damages caused by interdependence in critical infrastructures. It also introduces a Bayesian network as a tool to analyze critical infrastructure interdependence.



**Keywords** Critical Infrastructures, Interdependence, Disaster, Direct and indirect damage, Hurricane Sandy

Haraguchi, M., & Kim, S. (2016). Critical infrastructure interdependence in New York City during Hurricane Sandy. *International Journal of Disaster Resilience in the Built Environment*, 7(2), 133–143. http://doi.org/10.1108/IJDRBE-03-2015-0015

## 4.1. Introduction

At the end of October 2012, Hurricane Sandy caused enormous damages from the Caribbean Sea to the northeastern coast of the United States. Sandy caused more than 200 fatalities along its track (Kunz, Mühr et al. 2013). Even though Sandy was not the most severe storm event in terms of wind speed and precipitation, it produced tremendous economic damage, particularly in the United States. Kunz, Mühr et al. (2013) concluded that the total damage might exceed USD 100 billion, estimating direct damage to be between USD 78 and 97 billion and indirect damage to be between USD 10 to 16 billion primarily due to business interruption.

Many storms hit New York with higher winds than Sandy's 80-mile-per-hour peak wind gusts and many storms have brought more rain than the half inch that Sandy dropped in parts of New York. However, Sandy's storm surge was unlike anything seen before (New York City Government 2013). Its arrival on the evening of October 29 coincided almost exactly with high tide and generated a massive surge on the Atlantic Ocean and in New York Harbor. The storm surge caused flooding that exceeded the 100-year floodplain boundaries by 53% citywide (New York City Government 2013). Though both wind and storm surge by hurricanes produce damages in many cases, specifically the most damage resulted from storm surge in New York City during Sandy.

The indirect damage due to business interruption resulted primarily from interconnected risks within infrastructures. The concept of interdependence of risks is very important to formulate a strategy to reduce disaster risks. The interconnected risks of critical system failures may relate to catastrophic cascade effects due to functional interdependence or physical proximity. Heterogeneous networks, in general, are particularly vulnerable to attacks in that a large-scale cascade may be triggered by disabling a single key node (Motter and Lai 2002). Therefore, national disaster risk management strategies must address interdependence between different sectors of critical infrastructure. This interdependence is also enhanced by an increasing degree of economic integration. Mapping and modelling of complex risks enable policy makers to address hazards and their economic cascading effects that do not travel linear pathways(Radisch 2013).

Hurricane Sandy is a very important example of examining interconnected risks posed by disasters because it caused extensive damage to electric transmission and distribution infrastructures in the Northeast and Mid-Atlantic region of the United States. Both electric and petroleum infrastructures are critically interdependent with other infrastructures such as water, communication, transportation, food supply and private sector supply chains. For example, approximately 8,500,000 customers lost power at peak during Sandy (U.S. Department of Energy 2013). The hurricane also damaged the region's petroleum infrastructures. As of November 6 2012, two refineries in the path of Sandy, i.e. Hess Port Reading Refinery in Port Reading, New Jersey and Bayway Refinery Phillips 66 in Linden, New Jersey, were shut down. This resulted in the loss of 26.3% of the total operating capacity of 1,170,200 Barrels Per Day (U.S. Department of Energy 2012). The loss of the electricity and fuel sectors propagated to other sectors. Gas stations in New Jersey could not operate because of the outage. Three health care facilities in Manhattan and Brooklyn had to emergently evacuate all patients due to the outage.

The goal of this paper is to investigate the impact of Hurricane Sandy from the perspective of functional interdependence between different sectors of critical infrastructure and identify interconnectedness of risks posed by the natural hazard. The collapse of power utilities and petroleum infrastructures triggered failures in other infrastructure systems such as health care facilities, public transportation systems, the supply of necessities, and emergency facilities in the New York metropolitan area.

## 4.2. Literature Review

### 4.2.1. Methodology of Previous Studies

There are several ways to estimate the direct and indirect economic losses and damages induced by interdependent risks. Satumtira and Dueñas-Osorio (2010) review research in the field of infrastructure interdependence from the 1980's to 2010. They categorize four methodologies under mathematical models in the field: Agent-based, input-output, network or graph theory, and all other emerging models. One of the main approaches is to use the input-output model proposed by Leontief (1986). Indirect economic losses are usually quantified in terms of production losses in the affected region with the help of input-output models (Okuyama 2007). For example, Wei, Dong et al. (2010) deploy the inoperability Input-Output Model (IIM) to assess the impacts of supply chain disruptions. Wei, Dong et al. (2010) formulate an Ordered

Weighted Averaging Operator to evaluate the interdependence matrix, which is a key component of the IIM. Furthermore, Kajitani and Tatano (2014) investigate a method for estimating the production capacity loss rate (PCLR) of industrial sectors damaged by a disaster. They propose a method of PCLR estimation that considers the two main causes of capacity losses, namely damage to production facilities and disruption of lifeline systems. This study utilizes indirect damages of each sector to estimate the degree of functional interdependence between each sector. To estimate indirect damages of each sector, this study uses GIS mapping and compares the hypothetical damages calculated from the inundation areas with actual damages reported by government agencies.

### 4.2.2 Economic Losses through Interdependent Infrastructures

Some studies have investigated the damage of Sandy through direct and indirect economic losses. Kunz, Mühr et al. (2013) concludes that Hurricane Sandy is the second costliest hurricane in the history of the United States next to Hurricane Katrina. The direct economic losses are estimated between USD 78 and 97 billion in the US (Kunz, Mühr et al. 2013) while the direct economic losses in New York City are estimated between USD 15 billion (Cuomo 2012) and USD 19 billion (DeStefano 2012). By comparing Sandy with similar past events, Kunz, Mühr et al. (2013) calculate the value of power outage disruption to be USD 16.3 billion. Using the input-output approach and modeling sector-specific dependencies, Kunz, Mühr et al. (2013) quantify total business interruption losses to be between USD 10.8 and 15.5 billion.

### 4.2.3. Descriptions of the Damages for Each Sector

New York City Government (2013) summarizes the damages to various critical infrastructure: buildings, utilities, liquid fuels, healthcare, telecommunications, transportation, water and wastewater, and other critical networks. This section of the study encapsulates the damages outlined in a report by New York City Government (2013) while demonstrating interdependent features of critical infrastructures in various parts of damages. It also demonstrates the electricity sector played a crucial role in citywide critical infrastructures during Sandy.

Within the utility sector, the most damage was suffered by the electric system. The total number of New York electric customers who lost power as a result of Sandy eventually reached 800,000, which is equivalent to more than 2 million people. Physical damages to substations produced especially large disturbances. In total, about 370,000 electric customers in New York City were left without power due to network shutdowns and substation. The vulnerability of substations in networks was reported by various past studies that examined cascading failures in the power grid (Albert, Albert et al. 2004, Kinney, Crucitti et al. 2005). Damaged substations also led to stresses within the city's transmission system, which became another cause of power outages. As a result, 140,000 customers lost power.

In the building sector, Sandy flooded approximately 88,700 buildings, or 9% of the city's building stock. As an example of interdependent infrastructure, the vulnerability of building structures caused approximately 55,000 customers to lose power because of damage to electrical equipment in their buildings. The fuel sector also became the source of propagating risks to different sectors. Regional refineries were partially shut down before the storm to minimize damage to equipment. Storm surge also damaged electrical equipment at two of the six refineries, reducing regional refining capacity. Major pipelines were also closed for four days due to extensive power outages in New Jersey. This reduced total supply in the region by another 35 to 40%.

The waste management sector experienced fewer damages partly because the facilities housed vehicles that were moved out of the storm surge inundation area. In contrast, the larger waste disposal system was affected by Sandy. The Essex County Resource Recovery Facility preemptively shut down its boilers, and could not operate for a subsequent two weeks due to significant floods. Eventually, over 10% of its disposal capacity was lost.

Sandy's impact on the health sector was significant. Five acute care hospitals and one psychiatric hospital closed. Of these, three hospitals closed preemptively. Three other hospitals shut down due to the failure of electrical and mechanical systems including emergency power systems. In addition, residential providers, nursing homes, community-based providers also had significant damages due to flooding and power outages. For example, 500 community-based providers (5% of total providers) were located in inundated areas while 1200 providers (12% of total providers) were in areas that experienced power outages only. The impact of failures in the electricity sector on the health sector, one of the examples of interdependent critical infrastructure, was significant.

Sandy also enormously affected every transportation system. All six of the subway tunnels connecting Brooklyn to Manhattan, one tunnel from Queens to Manhattan, and one tunnel from Long Island City to Greenpoint were flooded. In addition, The PATH tunnels under the Hudson River and the railroad tunnels under the East River also were flooded. This shutdown of various transportation systems impacted about 8.6 million daily public transit riders, 4.2 million drivers, and 1 million airport passengers.

## 4.3. Methodology and Data

The damage to the critical infrastructures depends on the type of disaster and its temporal and spatial characteristics. From among these, the most critical factor affecting cascading infrastructure failure is a spatial characteristic of each sector. Therefore, this paper focuses on estimating the direct and indirect damages caused by Hurricane Sandy to each sector using GIS techniques. Here, we define direct damages as the physical damages caused by Sandy in each sector. The indirect damages were caused by functional problems such as power outage, overload, and impacts of failures in other sectors.

The total coastal areas of NYC inundated by Sandy were about 216.4 square kilometers. Since many parts of the city's critical infrastructures were within the inundated areas, the critical infrastructures were damaged directly by storm surge and wind. In addition, due to the cascading effects, the infrastructures were indirectly damaged. The sectors analyzed in this section are building, utility, healthcare, and transportation, due to data availability.

The direct and indirect relationship of each sector during Sandy is shown in Figure 4-1. The directly destroyed parts of an infrastructure indirectly damaged other parts of the infrastructure as well as other infrastructures. For example, due to the electric outage, gas stations could not provide fuels, even if they have sufficient gas supply. This paper defines the cascading effect as the process in which critical infrastructures were wrecked continuously as shown symbolically in Figure 4-1. The most critical infrastructure in NYC's case was the electricity sector because it indirectly affected other sectors such as transportation, telecommunication, and healthcare sectors; there is no specific alternative to overcome the problem. The degree of interdependence between each sector determines indirect damages triggered by a sector. The other way, if indirect damages of each sector are calculated, they could provide a guideline to estimate the degree of interdependence between each sector.

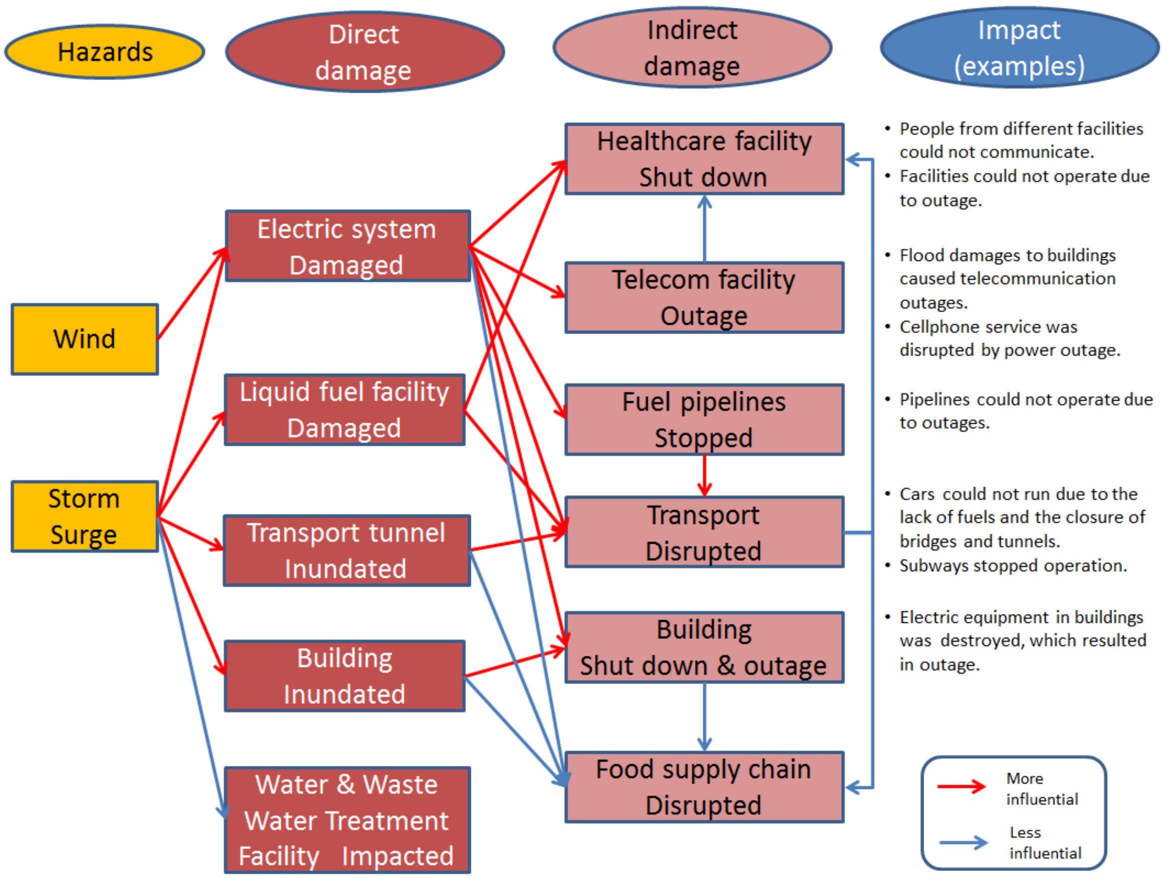


Figure 4-1:Schematic Features of Interdependent Infrastructures

In this study, the spatial information of each sector is used to estimate the damage. The areas that experienced direct and indirect damage in the electricity sector are estimated based on the causes of the electricity outage reported by New York City Government (2013). Directly damaged area is defined as one that lost power due to flooded transmission substation, flooded area substation, or preemptive shutdown. Areas that preemptively shut down facilities are considered directly damaged areas because they were flooded after the landing of Sandy. In contrast, indirectly damaged area is defined as one that lost electricity due to the transmission system overload. This study considers other sectors (not electricity) to be directly damaged if they are located in inundated areas on the flood map. Damages to other sectors are considered indirect if they were not inundated but affected by Sandy through interconnected infrastructures. For example, if a building is not inundated but it cannot pump drinking water up to higher floors without power, the damage is indirect. An electricity outage map is used to estimate the indirect damages to other affected sectors. The concept diagram is shown in Figure 4-2. The collected GIS data was summarized in Table 4-1.

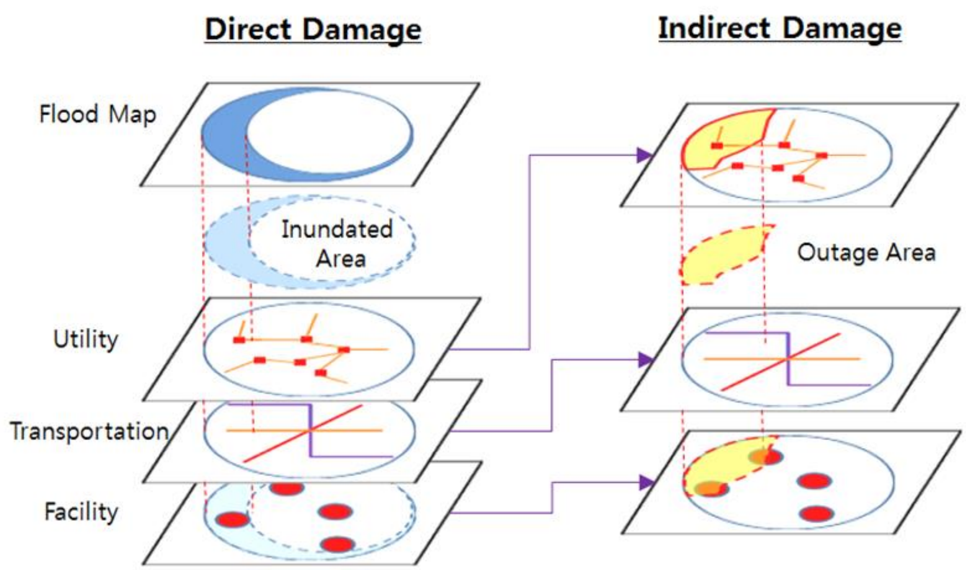


Figure 4-2:Concept diagram to estimate the direct and indirect damages

Table 4-1: GIS data sources

| GIS Data | Data sources |
|---|---|
| Inundated area | • FEMA Modeling Task Force(MOTF) (2013) |
| Building | • FEMA Modeling Task Force(MOTF) (2013) |
| Electricity outage territory | • New York City Government (2013) |
| Healthcare Facility | • New York City Government (2012) |
| Transportation routes (truck, bus, and subway) | • NYS GIS Clearinghouse (2013) |

## 4.4. Result of the Analysis

### 4.4.1. Estimation of direct and indirect damages

This study assumes the infrastructure within inundated areas to be directly damaged. We consider the infrastructure elements which were not flooded but lost power to be indirectly damaged. The direct and indirect damages are estimated using the spatial information of each sector (Figure 4-2). The estimated damages are summarized in Table 4-2 and mapped in Figure 4-3. The area of 173 square kilometers, which was about 12.7% of NYC, was affected by electricity outage or overload, including both the direct (9.9% of NYC) and indirect damages (2.8% of NYC). In the transportation sector, 10.7% of the total transportation mileage was directly damaged while 19.4% was indirectly damaged. In the health care sector, the direct damage was about 7.5% of the total number of facilities while the indirect damage was 2.4% of the total number of health care facilities. 7.0% of the number of buildings was built in the directly damaged areas while 16.8% were built in the indirectly damaged areas. Thus, in these sectors, the direct damage ranged from 7.0 to 10.7% and the indirect damage ranged from 2.4 to 19.4%. The variance of the direct damage in each sector is relatively small, while the variance of the indirect damage is large. This means that the degree to which one sector affects other sectors depends on the degree of interdependence among each sector. As a result, the transportation sector experienced direct damage by the storm surge the most, followed by electricity, health care, and building sectors. The most severely indirectly damaged sector by the electricity outage was transportation, which is followed by building, and health care sectors.

Table 4-2: Direct and indirect damages in each sector

| **Sectors** | **Direct damage** | **Indirect damage** |
|---|---|---|
| Electricity | 9.9% | 2.8% |
| Transportation | 10.7% | 19.4% |
| Health care | 7.5% | 2.4% |
| Building | 7.0% | 16.8% |

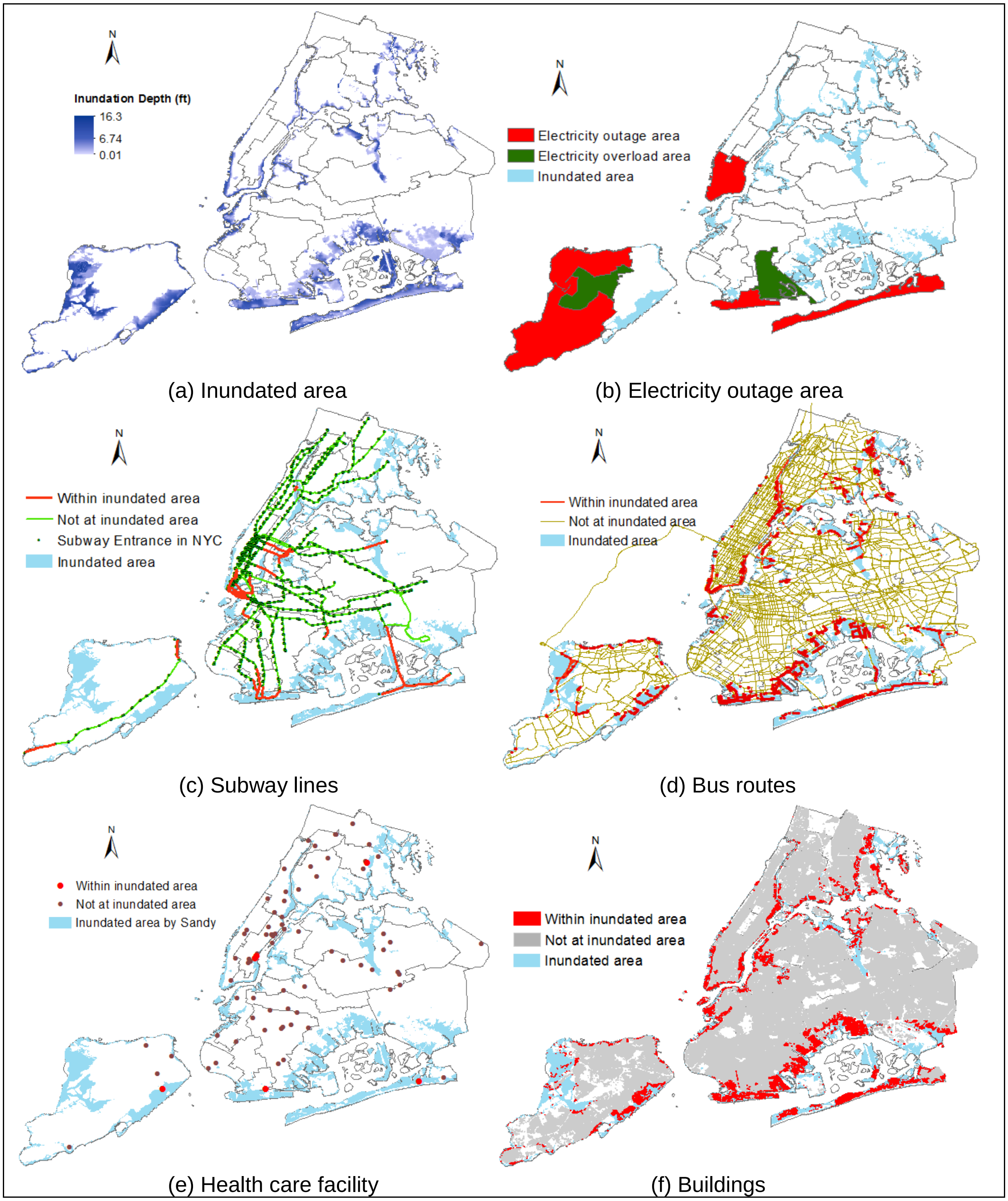


Figure 4-3: The spatial information of each sector affected by the storm surge in the NYC

#### 4.4.2. Comparing Damages Calculated Based on Inundation Areas with Actual Changes in Service Reported in Government's Reports

We compare the damaged calculated in Section 4.1 with numbers reported in New York City Government (2013). This paper estimates 7.0% and 16.8% in direct and indirect damages in the building sector. New York City Government (2013) reported 9% of the city's building stock was flooded, which is between our estimates of direct and indirect damages. In the healthcare sector, 8% of bed capacity and 17% of buildings of housing community-based providers are reported in New York City Government (2013). The percentage of affected bed capacity (8%) is close to 7.5%, which is our estimate in the direct damage of the health sector. New York City Government (2013) describes that east river crossing reduced by 86.8% on October 31, which is two days after Sandy. This number is not similar to our estimates, which are 10.7% for the direct damages and 19.4% for the indirect damage. Comparing our estimates with impacts in the transportation sector is not straightforward because the impact on the transportation sector includes various factors related to indirect damages. For example, New York City Government (2013) measures the impacts in the sector by referring to data such as changes in high way travel speeds and river crossings in addition to the number of impacted passengers, drivers and public transit riders. Therefore, it is essential to improve the methodology to estimate the impact in the transportation sector.

## 4.5. Discussion

This part of the paper demonstrates a Bayesian network (BN) model that can be built to analyze inoperability of critical infrastructure systems. BNs are probabilistic graphical models, which can represent relationships between variables even if the relationships involve uncertainty. BNs can integrate different types of variables from various sources into a single framework (Jensen 1996, Pearl 2014). Aung and Watanabe (2010) applied BNs to estimate interdependence and inoperability propagation in the Japanese critical infrastructure sectors.

A Bayesian Network consists of a directed acyclic graph of 'nodes' and 'links'. The relationships between nodes are described by conditional probability distributions that capture the dependences between variables. Bayesian Networks rely on Bayes' theorem to propagate information between nodes. Bayesian methodology is based on conditional probabilities: $P(A|B) = P(A, B) / P(B)$. Likewise, the probability of B given A can be calculated in the same manner, yielding what has come to be known as Bayes Law or Bayes theorem:

$$P\ (A|B) = P\ (B|A)\ P\ (A)\ /\ P\ (B) \qquad (1)$$

The network structure in Figure 4-1 is based on experts' analysis in New York City Government (2013). The included sectors in the Bayesian network are electricity, healthcare, transportation, water and waste water, and telecommunication. Nodes can be categorized into three layers: hazard, direct damages, and indirect damages. Nodes of hazards represent storm surge, including inundation and flooding. Nodes of direct damages represent direct damages to an electricity station, a liquid fuel facility, a transport tunnel, a building, a health care facility, and a water facility. Nodes of indirect damages indicate indirect damages to each sector. Figure 4-4 shows a constructed Bayesian network based on this network structure.

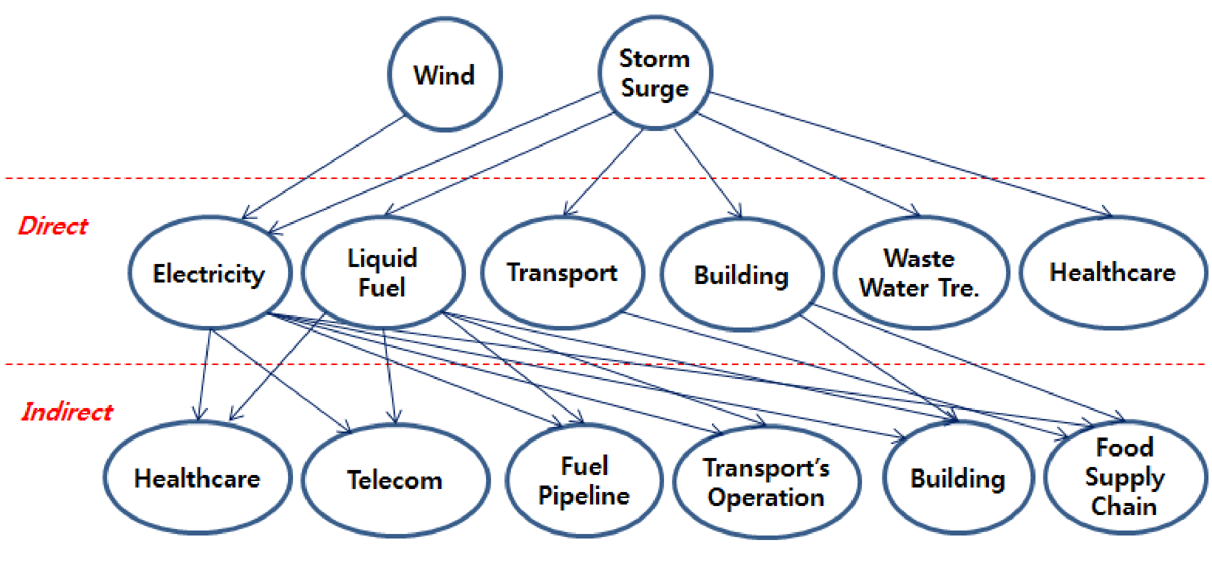


Figure 4-4: Bayesian networks for direct and indirect damages in critical infrastructures

BNs can derive an expected value from a countermeasure such as a backup generator. For example, backup generators are installed in hospitals in case of blackouts, in the hope that hospitals with generators will continue to operate (Figure 4-5). In this example, flood magnitude has conditional probabilities for three different scenarios: low, medium and high probabilities of inundations. In addition, the conditional probability table for an electricity substation is binary, i.e. whether operational or damaged.  Hypothetical values of back-up generators are assigned. Depending on expected values, the final result will show users whether a backup generator should be installed for each scenario of flood probabilities. BNs can also represent spatial differences in flood risks, using existing flood maps.

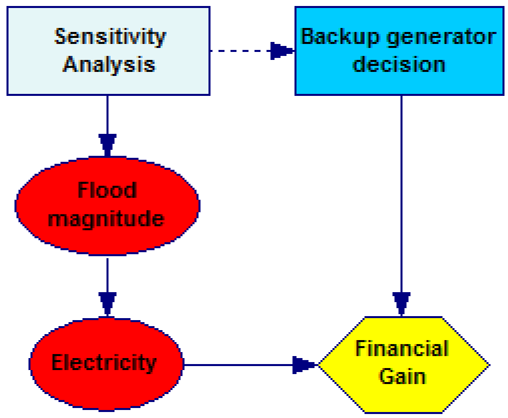


Figure 4-5: The benefit of a backup generator in electricity by the Bayesian network approach

## 4.6. Summary and Conclusions

Hurricane Sandy caused enormous economic damages because of the interdependent infrastructure systems in New York City. This study shows that the electricity sector plays a central role in citywide critical infrastructures, particularly in the healthcare, transportation, and liquid fuel sectors. This study also estimates direct and indirect damages by combining inundation maps with maps of each critical infrastructure. This study's estimates of damages are close to the damages reported by New York City Government (2013) in the building and health care sectors. In contrast, the direct and indirect damages in the transportation sector are not estimated well by our study because the damages in the sector are influenced by other external factors and are not easily measured.

The current plans proposed by New York City Government and relevant public-benefit corporations focus more on reducing direct damages than indirect damages. For example, New York City's building sector initiatives in New York City Government (2013) contain various methods to construct new buildings and retrofit old buildings in the floodplain to the highest resiliency standards. Considering the result of this study that the indirect damages to the building sector were larger than direct damages, new plans must reduce indirect damages with a focus on interdependence between sectors. For example, the electricity sector must reduce feeder segment size.

Studies that examine interdependent infrastructures face data collecting challenges because they require data from different sectors, which are sometimes spread over different jurisdictions. Rinaldi, Peerenboom et al. (2001) point out the lack of data in interdependent infrastructure studies. Also, future studies must estimate the economic damages caused by interdependent infrastructure risks. For example, in the transportation sector, approximately 8.6 million daily public transit riders, 4.2 million drivers, and 1 million airport passengers were impacted by the shutdown of not only the transportation system but also other sectors such as building and telecommunication sectors (New York City Government 2013). Future studies about Sandy must improve their methodology to estimate damages in the transportation sector caused by interdependent risks, for example, damages due to power outages. They also must address economic losses caused by interdependence. This study also suggests that a BN is an effective tool to represent functional interdependence of critical infrastructure. A Bayesian network can help estimate an expected value of a countermeasure, such as a backup generator in case of an outage.

# CHAPTER 5. BUILDING PRIVATE SECTOR RESILIENCE: DIRECTIONS AFTER THE 2015 SENDAI FRAMEWORK


## Abstract

During recent mega-disasters, such as the 2011 Great East Japan Earthquake and the 2011 Thailand floods, interdependencies in supply chains caused substantial economic damage, often exacerbated by vulnerable small and medium enterprises (SMEs). Therefore, a new global framework in disaster risk reduction, the Sendai Framework for Disaster Risk Reduction 2015-2030, mentions the role of the private sector in achieving a resilient society. However, the framework's statements are abstract and they need to be converted into actionable agendas. This paper identifies future directions for private sector resilience to disasters, focusing on business continuity. Even though business continuity has been regarded as a critical factor in conventional disaster planning, Business Continuity Management (BCM), articulated as a holistic management process, tends to be designed and implemented selectively by each organization. To address SMEs and supply chain resilience, this paper proposes a new type of BCM, a regional BCM based on Public-Private Partnership (PPP), and a new role for the insurance industry.



**Key Words**: Business Continuity Management (BCM), private sector resilience, supply chain resilience, small and medium enterprise, public-private partnership.



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## 5.1. Introduction

With economic development the loss of life caused by disasters is decreasing while economic damages are increasing (The Economist, 2012). For example, the Great East Japan Earthquake in 2011 led to production losses totaling 78.1 billion US dollars and Japan's gross domestic product lost 41.7 billion US dollars from March to May in 2011, which is 3.6% of Japan's typical economic output. Thailand's 2011 flood decreased the world's industrial production by 2.5% (UNISDR, 2012) and Thailand's GDP growth rate in 2011 declined by 75% (The World Bank, 2012). The direct economic losses in 2012 in the United States due to Hurricane Sandy were estimated to be between 78−97 billion US dollars and business interruption losses were between 10.8−15.5 billion US dollars (Kunz et al., 2013). The cost of disasters worldwide has reached an average of 250 billion to 300 billion US dollars every year (UNISDR, 2015).

The private sector plays a significant role in disaster risk reduction for the following reasons:

- The private sector reflects the vulnerability of the entire economy. Due to technological advances and globalization, companies and business operations are more interconnected than before.
- Government services and critical infrastructures, which support business activities, are interdependent on each other. As an example, due to the interdependent infrastructure systems, Hurricane Sandy in 2012 caused cascading failures of critical infrastructure in the New York metropolitan area (Haraguchi & Kim, 2014). The power outage disrupted other critical infrastructures such as hospitals, transportation, and telecommunication, causing damage costs of 16.3 billion US dollars (Kunz et al., 2013). These critical infrastructures are also increasingly privately owned or operated.
- In a networked society, socioeconomic structures become more interconnected. Consequently, during shocks and disruptions, the speed and area of "chain failure" has increased, which increases the possibility that a company in a safe area would be affected by failures of other companies in an area hit by a disaster. The complexity of the interconnected chains makes it difficult for a company to detect a source of vulnerability in advance. Due to these reasons, unexpected incidents have increased and economic damages per incident are increasing.

- Risk-insensitive investment causes catastrophic damages. For example, during the Thailand floods in 2011, more than 800 factories were damaged in 9 industrial parks, which were located near the flooded river (Haraguchi & Lall, 2015). The areas of these industrial parks used to be paddy fields, which were prone to flooding, but with lower damage exposure.
- However, the private sector is also a source of solutions. The private sector as a whole drives innovation and provides funding for major investment, which can potentially transfer a society to a resilient one. The role of the insurance industry is critical to transferring residual risks.

Stronger disaster risk management is also beneficial for companies for three reasons: it reduces uncertainty and strengthens confidence to cope with disasters; it opens the door to cost savings; and it provides an avenue for value creation (UNISDR, 2013).

Recognizing the importance of private sector resilience, the Sendai Framework for Disaster Risk Reduction 2015–2030, a successor of the Hyogo Framework and adopted in March 2015 during the Third United Nations World Conference on Disaster Risk Reduction, mentions it in several official statements. Table 5-1 summarizes statements in the Sendai Framework relevant to private sector resilience. As the guiding principle, the Sendai Framework states that disaster risk-informed investment in the public and private sectors is more cost-effective than post-disaster response and recovery.[4] One of the prioritized actions is to increase business resilience and protect productive assets throughout the supply chain.[5] In the section "Role of Stakeholders," SMEs are mentioned as targeted entities.[6] However, these statements are abstract and they need to be converted into actionable policy agendas. Therefore, this paper will provide implications as to how private sector resilience should be addressed after the Sendai Framework. A literature review was also done to provide a context for the setting.

[4] In Paragraph 19 (j) in the section III (Guiding principles)
[5] In Paragraph 30 (o) in Priority 3 (Investing in disaster risk reduction for resilience in the section IV (Priorities for action).
[6] In Paragraph 31 (b) in Priority 3 (Investing in disaster risk reduction for resilience) in the section IV (Priorities for Action) ; Paragraph 36 (c) of the section V (Role of stakeholders); and Paragraph 48 (f) of the Section VI (International cooperation and global partnership).

Table 5-1: Statements in the Sendai Framework 2015 – 2030 that addresses the private sector resilience.

| Items | Statements |
|---|---|
| Paragraph 19 (j) in the section III (Guiding principles) | "Addressing underlying disaster risk factors through disaster risk-informed public and private investments is more cost-effective than primary reliance on post-disaster response and recovery, and contributes to sustainable development." |
| Paragraph 30 (b) in Priority 3( Investing in disaster risk reduction for resilience) in the section IV (Priorities for action) | "Promote mechanisms for disaster risk transfer and insurance, risk sharing and retention and financial protection, as appropriate, for both public and private investment in order to reduce the financial impact of disasters on governments and societies, in urban and rural areas;"[7] |
| Paragraph 30 (o) in Priority 3( Investing in disaster risk reduction for resilience) in the section IV (Priorities for action) | "Increase business resilience and protection of livelihoods and productive assets throughout the supply chains. Ensure continuity of services and integrate disaster risk management into business models and practices." |
| Paragraph 31 (b) in Priority 3 (Investing in disaster risk reduction for resilience) in the section IV (Priorities for Action) | "Promote the development and strengthening of disaster risk transfer and sharing mechanisms and instruments in close cooperation with partners in the international community, business, international financial institutions and other relevant stakeholders." |
| Paragraph 36 (c) of the section V (Role of stakeholders) | "Business, professional associations and private sector financial institutions, including financial regulators and accounting bodies, as well as philanthropic foundations, to: integrate disaster risk management, including business continuity, into business models and practices via disaster risk-informed investments, especially in micro, small and medium-sized enterprises; engage in awareness-raising and training for their employees and customers; engage in and support research and innovation as well as technological development for disaster risk management; share and disseminate knowledge, practices and non-sensitive data; and actively participate, as appropriate and under the guidance of the public sector, in the development of normative frameworks and technical standards that incorporate disaster risk management;" |
| Paragraph 48 (f) of the Section VI (International cooperation and global partnership) | "The United Nations Global Compact, as the main United Nations initiative for engagement with the private sector and business, to further engage with and promote the critical importance of disaster risk reduction for sustainable development and resilience;" |

Source: The UN General Assembly (2015)

## 5.2. Literature Review

### 5.2.1. Resilience in the Private Sector

It is important to consider the concept of resilience and why there is a need for additional research in the context of the private sector. Resilience is defined as "the ability to resist and respond to a shock and disruption, either internal or external, and recover once it has occurred (Annarelli & Nonino, 2015)." The private sector's resilience is a collection of organizational resilience of each company through supply chain resilience, and it is laid among societal, community, and public sector's resilience (Figure 5-1).

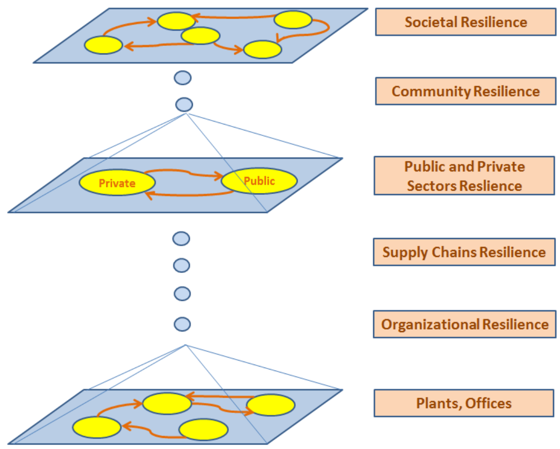


Figure 5-1: Layers of Resilience

Annarelli and Nonino (2015) identifies the following four important components for organizational resilience:

- Resilience is a system's capability to return to its original state or to a new, more desirable one (Carvalho, Cruz-Machado, & Tavares, 2012).
- Resilience is static and dynamic (Rose, 2004, 2007)
- Resilience should be a strategic initiative (Sheffi & Rice Jr, 2005)
- Resilient organizations are anticipatory responders (de Oliveira Teixeira & Werther, 2013).

To increase organizational resilience of a company, researchers suggest:

- The initiative of building resilience should be the strategic core of their operations in companies in order to change the way a company operates and increase its competitiveness (Sheffi & Rice Jr, 2005).
- Companies can also increase their resilience by either building in redundancy or building in flexibility (Sheffi & Rice Jr, 2005). Investing in flexibility offers additional benefits for daily operations while investing in redundancy purely increases costs (More & Subash Babu, 2008; Sheffi & Rice Jr, 2005; Stevenson & Spring, 2007). Building in redundancy can be achieved by increasing inventory, having alternative suppliers for the same parts, and duplicating production and IT systems. Thus, building in redundancy will incur costs to a company. In contrast, building in

flexibility means having workable alternatives in any situation (Sheffi, 2005). One example of building in flexibility is standardization of parts and production systems so that they are interchangeable and can be used when a disruption occurs. In this sense, building in flexibility not only bolsters the resilience of an organization, but it also creates a competitive advantage in the market because standardization often reduce costs (Sheffi & Rice Jr, 2005). Investments in flexibility thus can be justified on the basis of normal business standards even without considering the benefits of risk mitigation and cost avoidance (Sheffi & Rice Jr, 2005).

The question is how to increase flexibility (More & Subash Babu, 2008; Stevenson & Spring, 2007). Sheffi and Rice Jr (2005) suggest that flexibility can be achieved by addressing five essential elements of any supply chain: “Material flows from *supplier* through a *conversion process*, then through *distribution channels*. It is controlled by various *systems*, all working in the context of the *corporate culture*.” In each of five phases, if resources and inputs are interchangeable, for example, under modular design and delayed differentiation, flexibility can reduce risk, especially for interruptions involving discontinuities in raw material availability and component supply (Kleindorfer & Saad, 2005). Stevenson and Spring (2007) also argue that flexibility can be combined with proactive means of reducing unwanted supply chain uncertainty such as the roles of supply chain design, supply chain collaboration and inter-organizational information systems.

Though it is not easy to measure the results of increased flexibility with traditional accounting and risk management tools, investment in flexibility can be justified based on conventional business standards such as increased sales, reduced costs and increased competitive advantage. Firms can benefit from by introducing flexible operations (Sheffi & Rice Jr, 2005). In this sense, when companies build flexibility in order to respond to demand and supply volatility, they are also building in resilience and vice versa (More & Subash Babu, 2008; Sheffi & Rice Jr, 2005; Stevenson & Spring, 2007). For example, a local supplier that has reactive capacity and can respond quickly to demand changes can supplement a low-cost overseas supplier (Sheffi & Rice Jr, 2005). Such flexible capacity can supplement the first supplier overseas not only during disruptions but also during volatile demands.

### 5.2.2. The Role of BCM for the Resilience in the Private Sector

Business continuity is defined in the ISO31000:2009 as "capability of the organization to continue delivery of products or services at acceptable predefined levels following a disruptive incident" and a plan for business continuity is called Business Continuity Planning (BCP). In order to make a BCP feasible, organizations should implement it with Plan-Do-Check-Act (PDCA) cycle as BCM. BCM is defined in the ISO22301 as "holistic management processes that identify potential threats to an organization and the impacts to business operations those threats, if realized, might cause, and which provides a framework for building organizational resilience with the capability of an effective response that safeguards the interests of its key stakeholders, reputation, brand and value-creating activities (International Organization for Standardization, 2012)." Therefore, the role of BCM is to implement PDCA cycle in order to continuously improve the management system for addressing dynamic disaster risks. It should be noted that BCM is different from a BCP in the sense that a BCP is a structured action plan to be followed during and after disasters, often made as a document. In contrast, BCM is a management system, which requires constant input of management resources. Thus, a BCP is one of outputs by implementing a BCM program. The advantage of BCM is in its capacity to help an organization to identify a crisis situation, flexibly manage it, and keep the critical knowledge within an organization (Venclova, Urbancova, & Vydrova, 2013). By contrast, one of the main disadvantages is the difficulty of integrating its implementation into organizational cultures (Venclova et al., 2013). BCM is originally designed to enhance organizational resilience. This now produces another problem in the interconnected economy, which will be discussed later in this paper.

## 5.3. Objectives of the Paper

This paper argues that SMEs and supply chains are critical to increasing the resilience in the private sector while referring to the case studies of the Great East Japan Earthquake and Tsunami in 2011, Thailand floods in 2011, Hurricane Katrina in 2012, and other instances. The objective of this paper is to identify future directions for private sector resilience to disasters, focusing on business continuity, by:

(1) discussing vulnerability of SMEs and supply chains in the private sector.

(2) demonstrating the limitations of individual BCM and evaluating the effectiveness of a regional BCM based on PPP to address SMEs and supply chains resilience; and

(3) proposing a new role for the insurance industry.

The focuses of this study are consistent with previous studies. Through a literature survey, Annarelli and Nonino (2015) identified seven future research directions on organizational resilience as Table 5-2. Among directions proposed by Annarelli and Nonino (2015), this paper will examine #3 (Resilience in Small Medium Enterprises), #4(Restorations models for the supply chain and operational processes), and #7(Strategic approach and dynamic capabilities for becoming a resilient organization).

Table 5-2: Future research directions for organizational resilience

| |
|---|
| 1. Theory testing for design, implementation, and improvement of processes to enhance organizational resilience<br>2. Measurement of organizational and operational resilience<br>3. Resilience in Small Medium Enterprises<br>4. Restorations models for the supply chain and operational processes<br>5. Impact of introducing of information systems on organizational resilience<br>6. Anticipatory innovation to enhance processes' resilience<br>7. Strategic approach and dynamic capabilities for becoming a resilient organization |

Source: Annarelli and Nonino (2015)

## 5.4. Discussion: What are Challenges and How can They Be Addressed?

### 5.4.1. Supply Chain Vulnerabilities: SMEs as its Bottlenecks

Supply chains contribute to the global losses posed by local disasters. For example, as a result of chained disruptions from the Great East Japan Earthquake and Tsunami in 2011, "unmanaged" concentrated risks became visible, particularly in 4$^{th}$ tier suppliers and under. Most of them are SMEs without a BCP. Additionally, due to the shortage of parts from Japan, General Motors had to stop operations at a factory that manufactures pickup trucks in Shreveport, Louisiana in the United States. Another example is Toyota's case during Thailand floods in 2011. Their critical supplier was damaged by floods, which resulted in disrupting the entire supply chain even though Toyota's assembly plant was not at all damaged (Haraguchi & Lall, 2015). During the Thailand flood, even reinsurance risk analysts had ignored the interconnectedness of global supply chains over past decades (Merz, Vorogushyn, Lall, Viglione, & Blöschl, 2015). In April 2011, volcanic eruption in Grímsvötn Iceland caused supply disruptions of parts from Ireland to two main factories in Japan, which had to stop operations for a few days.

Economic damages caused by the interconnected economy are increasing. Direct and indirect economic damages of the Great East Japan Earthquake in 2011 still caused bankruptcies in 2015 (Tokyo Shoko Research, 2015). Approximately 90% of the bankruptcies caused by this earthquake can be attributed to indirect damages through the supply chains. This number is more than the amount of the Kobe Earthquake in 1995, when indirect bankruptcies were less than 50%. This indicates that supply chain vulnerability may translate into increasing losses in an interconnected economy. Other studies, such as Liverman (2015), point out the importance of assessing climate impacts within an interconnected global economy.

SMEs are one of primary sources of vulnerabilities in supply chains. This study will characterize SMEs in contrast to large companies. SMEs are defined in this study as businesses with fewer than 249 employees. During the Great East Japan Earthquake in 2011, SMEs caused substantial disruptions in supply chains in the manufacturing sector, called a Single Point of Failure (SPOF). A SPOF is originally used in the field of information systems and refers to a system component which, upon failure, renders an entire system inoperable. If critical nodes and roots in a supply chain network such as assembly plants or critical suppliers are damaged, significant losses would occur, leading to a SPOF (Haraguchi & Lall, 2015; Watanabe, 2015). Therefore, it is important to detect vulnerable points quickly in the case of emergency. The lack of effective partnership with different suppliers would lead to supply chain-induced losses. Also, service disruptions in lifelines such as power grids and water supply will affect the performance of entire supply chains (Haraguchi & Lall, 2015).

In the case of supply chains, SMEs have specialized technologies and high market share and are positioned among the lower-tier (e.g., 3rd tier) suppliers. SMEs have a common characteristic, resource scarcity, which sets them apart from large organizations (Storey, 1994; Sullivan-Taylor & Branicki, 2011). Partly because of resource scarcity, SMEs tend not to have a BCP compared to large companies. In Japan, less than 10 % of SMEs have a BCP (Mitsubishi UFJ Research and Consulting, 2012; NKSJ Risk Management, 2012). In six cities of the Americas[8], small businesses have the lowest rate of BCPs (14%) compared to large businesses (44.9%) (Sarmiento et al., 2014).

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[8] Bogotá (Colombia), Miami, Florida (United States), San José (Costa Rica), Santiago (Chile), Kingston (Jamaica), and Vancouver (Canada)

Small and medium enterprises face challenges to implementing a BCM program. During the Japanese earthquake in 2011, SMEs became SPOFs because in a highly specialized market many SMEs in the lower-tier suppliers accounted for higher market share (Watanabe, 2015) and because they could not be substituted when they were impacted by disasters. During the event, local governments and parent companies tried to reach SPOFs, but they could not due to the lack of regular communications even during normal times (Watanabe, 2015). As a result, approximately 70% of the bankrupted companies caused by the Japanese earthquake in 2011 have been SMEs (Databank, 2014).

The Thai floods in 2011 also heavily impacted SMEs. Before the floods, the total number of SMEs in Thailand was 3 million, accounting for 99.6 percent of all enterprises and 77.9 percent of all employment in 2010(Abe & Ye, 2013; Perwaiz, 2015). Because of the 2011 flood, approximately 550,000 SMEs incurred direct and indirect damage, estimated at 71.1 billion Thai Baht (THB) per month, with 2.3 million jobs lost (Abe & Ye, 2013; Perwaiz, 2015).

Small and medium enterprises should get more attention in the discussion of the private sector's resilience for the following reasons. SMEs typically represent 99% of all enterprises in Europe and America(Ingirige, Joness, & Proverbs, 2008; Savage, 2002). SMEs significantly contribute to the economic vitality of cities, states and countries due to their large number of employees (Robbins, Pantuosco, Parker, & Fuller, 2000). SMEs are spatially interconnected and dependent, and consist of major parts of supply chains in some sectors (Ministry of Economy Trade and Industry, 2011). However, most SMEs do not consider a BCP even though guidance exists (Ingirige et al., 2008). Therefore, SMEs face greater short-term losses after a natural disaster and are more vulnerable than larger businesses. Many SME owners operate and reside locally, which means that their business and residence are exposed at the same time. In addition, SMEs cannot easily insure against disasters due to their funding limitations (Ingirige et al., 2008; UNISDR, 2013).

Ingirige et al. (2008) attribute SMEs' inability to effectively react to disasters to the following factors: lack of planning, vulnerability to cash flow interruptions, lack of access to capital for recovery, ineffectual interactions with national agencies, infrastructure problems impeding recovery (Runyan, 2006), individual attitudes and organizational culture (Petts, 1998), access to expertise, business sector and perceived exposure to risk (Yoshida & Deyle, 2005). Some of these factors, such as ineffective interactions with agencies, individual attitudes and organizational culture can be addressed by BCM. Because SMEs lack resources, governments should provide adequate assistance to SMEs, such as helping with preparedness and promoting disaster insurance coverage (Abe & Ye, 2013).

### 5.4.2. The Limitations of Individual BCM and Effectiveness of Regional BCM Based on PPP

Considering functional interdependence and geographical concentration, all key organizations in supply chains need to have a BCP and implement it as BCM systems with a PDCA cycle in their management and daily operations. However, business activities, even with BCM, were disrupted in much wider areas for much longer periods than ever before during the recent disasters such as the 2010 volcanic eruption in Iceland, the 2011 Great East Japan Earthquake, and the 2011 major flood in Thailand. This proves that installing BCM in an individual company does not sufficiently address interdependencies between organizations in supply chains. The interdependencies caused chain-failures with wider repercussions in economic activities. During the recent natural disasters, the BCP of each company was activated with a different time frame and based on different criteria that each organization had set at their planning phase. These inconsistencies among interrelated organizations caused inefficiencies and avoidable conflicts in response and recovery activities. In order to avoid such chaotic situations in disaster response and recovery activities, all stakeholders in a region or a supply chain need a scheme for cross-organizational decision-making during a catastrophic disaster. Consequently, stakeholders, including regulators and investors, have become increasingly concerned about vulnerability in business continuity. As a result, they are putting pressure on companies through such measures as contractual requirement, interest rate of lending, investment policies, and disclosure of hidden risks (UNISDR, 2013).

Due to the interdependencies between multiple stakeholders, the scope of a BCM program needs to be expanded (Steyer & Gilbert, 2013; Watanabe, 2009, 2015). In the public sector, a local government should cooperate with external partners such as the central government and agencies, local communities, and neighboring local governments. In the private sector, enterprises should expand the scope of their BCPs to involve their corporate group enterprises, business partners, industry associations, and local communities. In expanding the scope of BCM, the public and private sectors can cooperate through the public-private partnership (PPP). Therefore, we propose a new type of BCM, a regional BCM based on PPP.

The primary objective of a regional BCM based on PPP is to maintain business continuity in the local economy during disasters. An effective regional BCM should perform the following functions.

- First, a regional BCM should promote coordination between different stakeholders and suppliers to prevent supply chain disruptions. In order to avoid fragmented implementation of BCPs among each company and government agency, a regional BCM should have a platform for information sharing and collaboration and should even promote joint planning of BCPs among different stakeholders.
- Second, a regional BCM should conduct joint public-private risk assessments. In both the Great East Japan Earthquake in 2011 and Hurricane Sandy in 2012, the breakdown of electricity generation and supply systems caused substantial economic damages. This corresponds with the survey conducted by Sarmiento, Hoberman [28], which demonstrated that more than half of the 1,197 businesses identified disruptions owing to power outages as a main concern during disasters. Therefore, a regional BCM should identify key risk amplifiers in an interconnected critical infrastructure. In addition, the public sector needs to promote research on disaster loss data and multi-hazards risk assessments [42]. This will prevent narrowly focused preparation based on each specific hazard.
- Third, a regional BCM should provide economic and financial incentives for companies to implement a regional management system. Particularly, because SMEs lack financial and human resources to implement BCM systems, it is critical that a regional BCM should serve as an intermediary (Watanabe, 2009, 2015).

A regional BCM with above functions can increase private sector resilience, particularly by addressing SMEs and supply chain resilience. Because SMEs lack the capacity to undertake their own risk analysis, a regional BCM should promote sharing open and accessible risk information, insurance options and disaster loss data, conducting joint public-private risk assessments (UNISDR, 2013), and serve as an intermediary to provide SMEs economic and financial incentives to implement a BCM program(Watanabe, 2009, 2015). A reginal BCM also contribute to the resilience in supply chains. Sharing information among suppliers and stakeholders would reduce the lack of coordination during disasters. Zsidisin, Melnyk, and Ragatz (2005) finds that BCM in supply management can address supply risk a priori with broader approaches while relying on flexible operations rather than relying solely on building in redundancy. This is consistent with Sheffi (2005)'s claim that building in redundancy incurs costs and will not be meaningful unless it is needed in the case of a disruption while building in flexibility will yield benefits for day-to-day operations. A regional BCM can also enhance upper level of resilience, namely societal resilience, as a whole. If governments and companies identify areas to be recovered as a priority in a joint risk assessment of a regional BCM, the local community and economy is likely to recover more quickly. The National Research Council (2011) found that local-level PPP is essential to the development of community resilience in the United States, which include public and private sectors resilience. Community resilience is also necessary to secure interoperability vertically and horizontally for supply chains.

A regional BCM  is already implemented in practice. It is called “Area BCM” in Japan International Cooperation Agency (JICA) (Hitoshi Baba, 2014; Hitoshi Baba & Shimano, 2015). Area BCM refers to “the efforts of an area that aims to prevent economic stagnation of the targeted area regardless of the circumstances (Hitoshi Baba & Shimano, 2015).” “Area BCM” has been implemented to enhance regional information sharing through the Area-BCM Project for the Association of Southeast Asian Nations (ASEAN) countries by JICA since February 2013. The JICA’s project with industry complexes gained wide interests among the private sector. Three pilot sites were selected and several workshops have been initiated in Indonesia, the Philippines, and Vietnam (H Baba, Watanabe, & Miyata, 2015). Through this process, participating organizations have shared risk information among local stakeholders and discussed potential impacts of natural disasters.

### 5.4.3. A New Role for the Insurance Industry in Private Sector Resilience

Small and medium enterprises reluctant to formally consider natural hazard risks in their supply chains may consider business interruption insurance, or may count on help from the government in the event of a disaster. The cost of such insurance is now increasing as insurance and re-insurance companies re-examine their collective exposure to such events across multiple geographies. Government may be an avenue to buffer losses, but reliable and rapid support from governments in the event of a disaster can rarely be counted on. With the Thailand example, it was clear that given the scale of the disaster the Thai government moved to help with infrastructure and relief programs to protect its national export economy. However, this did not really help those who relied on Thai exports for their production and marketing supply chain. A possible recourse in that situation is to rely on suppliers in low risk areas and to insure each supply contract for disruption, if you are a buyer. However, this leads to an added cost, that most SMEs may be hard pressed to justify staying competitive. On the other hand, if the SME is a supplier for a disrupted supply chain, it may find it useful to insure its operations so that contracts lost during a disruption and after can be covered by purchases and shipments from other markets. However, insurance pricing often does not properly reflect risk levels or provide an adequate incentive for risk-sensitive business investment, particularly in low and middle income countries (UNISDR, 2013). For example, in China, only 3 percent of properties are insured against earthquakes and 5 percent against typhoons and floods (UNISDR, 2013). In addition, to avoid catastrophic losses to insurance companies, reinsurance and catastrophe bonds are useful at an insurance company and at a state level, respectively. In this way, response and relief efforts of heterogeneous small and large businesses can be securitized. After all, the insurance sector is playing an emerging role in increasing private sector resilience.

## 5.5. Conclusion and Implications

The 2011 Japanese earthquake, the 2011 Thai floods, and Hurricane Katrina in 2012 show that these three countries face similar types of challenges in managing disaster risks in the private sector. The private sector, especially SMEs, faces supply chain vulnerabilities as well as asset exposure in the face of a natural or man-made disaster. SMEs' vulnerability causes disruptions and become SPOFs. For relatively low probability, but high impact and chronic events may occur as long term supply contracts for raw material or sales are disrupted. In fact, disaster losses worldwide are dominated by low-probability high-impact events (Noy, 2015). Information on such events is very limited, and hence it is also difficult to do scenario analyses as to the possible impacts for a SME or even for a larger company (Mechler, Linnerooth-Bayer, Hochrainer, Pflug, & Pflug, 2006). Redundancy in suppliers, such as multiple-sourcing, or in operational facilities and inventory can increase resilience but can be costly and limit competitiveness. These factors contribute to the reluctance of many SME and private sector players to formally consider natural hazard risks in their supply chains and operational processes. Therefore, it is critical to address SMEs' needs and supply chain resilience. To do so, this paper proposes a new type of BCM, a regional BCM on PPP, and a new role of the insurance industry.

An individual BCM is facing limitations in an interconnected economy. Even if an assembly plant of a multinational manufacturing company is safe with BCM, they have to stop their operations if their small critical supplier at the lower tier without effective BCM is damaged by disasters and cannot ship their specialized parts. However, a regional BCM can address interdependencies by including multi-stakeholders and preparing for disasters. Because SMEs lack resources, a regional BCM needs to include SMEs to share risk information, transfer knowledge, and provide SMEs a financial incentive to implement a BCM program. Not only sharing risk information but also transferring knowledge in disaster risk management is critical to increasing capacities in resilience of SMEs. This proposal is consistent with previous studies. For example, Ingirige et al. (2008) propose participatory approaches "to facilitate a process of knowledge transfer between the government policy makers, SME associations, supply chain associates and the targeted SMEs." Because this knowledge transfer is through "a continuous process of engagement between the various elements of the SME network (Ingirige et al., 2008)," this participatory approach can be done through a regional BCM. Based on the results of quantitative analyses of survey data from 230 small businesses in Duval County, Florida, Yoshida and Deyle (2005) also concludes that partnership between local governments and SMEs potentially offer an opportunity for successful implementation of hazard mitigation activities with SMEs. A regional BCM can include SMEs in the platform, which would increase horizontal and vertical interoperability in supply chains. Implementing a regional BCM program including SMEs in supply chains contributes to building in flexibility proposed by Sheffi (2005) because by sharing information and communication platforms, they can detect a disruption quickly and foster speedy corrective actions. To detect a disruption in supply chains, it is critical to maintain communication and information sharing among stakeholders during normal times. As a limitation of a regional BCM, supply chains from different regions would require a BCM program that covers stakeholders from different regions. However, industries that tend to construct their supply chain networks in concentrated industrial clusters, such as the automobile industry, can greatly benefit from a regional BCM. Steyer and Gilbert (2013) highlight multiple potential obstacles of BCM, such as unclear accountability, different cultures and modes of operation, and ambiguity concerning the nature, scope and membership of the partnership. As the discussions of Steyer and Gilbert (2013) are based on the context of a pandemic, future studies must examine obstacles to implement a regional BCM program in the context of natural or man-made disasters.

The review of the Sendai Framework shows that new opportunities exist for the insurance industry to increase private sector resilience. An emerging trend is parametric insurance products that provide financial cover linked to an extreme event, without directly assessing losses for the insured. These products provide an opportunity for lower cost cover with rapid settlement and a choice of strike and limit thresholds per unit of coverage purchased. However, they introduce a certain amount of basis risk, in that an affected party may not get covered, or may be paid when they have not been exposed, due to spatial variability of outcomes. They would potentially allow those exposed to supply chain risk to purchase appropriate cover, even if their suppliers, but not their assets, were directly located in the affected area, simply by purchasing units of the index. Given the regional nature of the index insurance product, clustering of claims could also potentially be reduced. This suggests a market creation opportunity in the insurance market. In addition to market opportunity, there is ultimately an opportunity for greater transparency in estimating natural hazard risks, their near term prediction, and the prediction of their supply chain impacts. Furthermore, there is a favorable opportunity to use this information in a decision framework to support market development for risk management by government agents, insurance providers, and supply chain analysts focused on the private sector.

# CHAPTER 6. FLOOD RISKS AND IMPACTS: FUTURE RESEARCH QUESTIONS AND IMPLICATION TO PRIVATE INVESTMENT DECISION-MAKING FOR SUPPLY CHAIN NETWORKS

## Abstract

The goal of this paper is to investigate the impact of floods on the global economy through supply chains, and to propose what components should be considered to measure supply chain risk. This study examined Thailand's 2011 flood since it is the most notable example of the impact of floods both on industries and the whole economy. Since the prolonged floods affected the primary industrial sectors in Thailand, i.e., the automotive and electronics industries, the impact on the whole economy was devastating. The impact of natural hazards on the supply chain is increasing. However, the impact on each firm that is exposed is different depending on how well they are prepared and how they respond to the risks. Designing supply chains in a more resilient way will ultimately reduce risks to the economy. Comparing different supply chains and industries' structure in the case of Thailand's flooding, the study identified the factors in private investment decision-making, such as *locations of facilities, alternate locations of production, the diversified sources of procurement, emergent assistance from other partner companies in the same supply chain,* and *degree of the recovery of customers* and proposed potential questions and a hypothesis for future research.

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## 6.1. Introduction

Floods on one side of the earth affect the economy on the other side of the earth through global supply chain networks. Today's global supply chain has achieved cost reduction by reducing inventory, shortening transportation timelines, and streamlining production systems. However, with lean and complex supply chains, there is much more susceptibility to systemic or aggregate risk, a financial term used to describe a risk originating from one node of a financial network which then harms the entire financial market. This notion of risk is applicable to supply chains. While a more efficient production and transportation system is more capital intensive and cost efficient, in the event of a natural disaster, the entire system may suffer disruption and break down. The Economist (2012)reported that while death rates from natural disasters have been falling, their economic cost continues to increase drastically. This cost includes place-based impacts and supply chain impacts. However, the latter have not been systematically reported or broken out.

According to Bolgar (2007), Accenture, a global management consulting firm, revealed that 93% of the companies studied consider supply chains as their top priority. Further, 30% of the companies attributed 5% of their lost revenue to the disruption of their supply chains. Supply chains are important, not only for a company but also for a nation. For instance, in January 2012, the Obama administration released the National Strategy for Global Supply Chain Security, which focuses on energy, container shipment, and cyber networks. For both companies and governments, weather-related hazards are one of the biggest sources of risk to the supply chain. A studied carried out by Zurich Financial Services Group and Business Continuity Institute (2011) revealed that 51% of supply chains were affected by adverse weather over the past year. 49% of businesses lost productivity from such disruption, while their cost increased by 38% and their revenue decreased by 32%.

Therefore, the objective of this study is (i) to investigate the impacts of floods on supply chains using the case of Thailand's 2011 flooding focusing on automobile and electronics industries; and (ii) To propose components that should be considered in measuring supply chain risk by proposing future research questions.

## 6.2. Reviews of Important Concepts and Indices

In this section, we review some concepts to provide a context for an analysis of the Thailand floods of 2011 and other cases related to the impact of floods on supply chain networks.

### 6.2.1. Direct and Indirect Damages

There are a number of definitions of damage caused by disasters (See for example, Rose (2004)). Yet, Table 6-1 is the common understanding among existing studies (Jonkman, Bočkarjova, Kok, & Bernardini, 2008). In this study, direct damage refers to the physical damage by natural hazards to facilities or equipment while indirect damage refers to the damage which is not physically damaged by natural hazards to facilities or equipment but is caused by ripple effects.

Table 6-1: Different aspects of flood damages.

| | Tangible and Priced | Intangible and unpriced |
|---|---|---|
| **Direct Damage** | •Residences<br>•Capital assets and inventory<br>•Business interruption (inside the flooded area)<br>•Vehicles<br>•Agricultural land and cattle<br>•Roads, utility and communication infrastructure<br>•Evacuation and rescue operations<br>•Reconstruction of flood defenses<br>•Clean up costs | •Fatalities<br>•Injuries<br>•Inconvenience and moral damages<br>•Utilities and communication<br>•Historical and cultural losses<br>•Environmental losses |
| **Indirect Damage** | •Damage for companies outside the flooded area<br>•Adjustments in production and consumption patterns<br>•Temporary housing of evacuees | •Societal disruption<br>•Psychological Traumas<br>•Undermined trust in public authorities |

*Source*: Jonkman, S.N., et al (2008)

### 6.2.2. Time to Recovery and Financial Impact

Second, the performance indices that measure the impact of a disaster on supply chains are reviewed. Simchi-Levi (2012) proposes the Risk Exposure Index, which assesses a cost induced by a potential disruption based on the Time to Recovery (TTR) for each level or node, and the resulting Financial Impact (FI). Those individual risk components are then summed up to obtain a comprehensive FI for the entire supply chain. There are several aspects of TTR. For example, time to resume operations, even partly, if a facility has been stopped, is a major indicator of resiliency that has frequently gained attention in the real business world. Time to return to the “pre-disaster” level of production can also be an important indicator in terms of the real impact of disruption. In the real world, Cisco Systems, Inc. has already adopted this notion of TTR, which is "…based on the longest recovery time for any critical capability within a node, and is a measure of the time required to restore 100% output at that node following a disruption(O'Connor, 2009)." Thus, to measure resiliency of supply chains or impacts of floods to supply networks, this paper will focus on TTR, the time needed for both part and full restoration.

Regarding the financial impact of the floods, the operational profits from the financial statements of a company as affected by the amount of extraordinary losses caused by disasters are of particular interest. This approach, that examines financial performance to see resiliency and robustness of supply chains, is similar to the trends in businesses. For example, Gartner, which is the leading information technology research company, have annually published Supply Chain Top 25 ranking since 2005. In 2012, Gartner attempted to measure resiliency of supply chain. The company assumed that companies with good and steady financial performance are more likely to manage supply chain than companies with unstable performance, though they did not examine TTR (Hofman & Aronow, 2012).[9]

### 6.2.3. Perspectives for Analyzing Supply Chain Resiliency and Robustness

Third, the concepts that are needed to analyze product and process features are introduced. This study uses the four perspectives proposed by Fujimoto (2011): *dependence*, *visibility*, *substitutability*, and *portability*. The first perspective is dependence on suppliers. Extreme dependence on one supplier's product can make the supply network vulnerable. The second is *visibility of supply chains.* If the downstream companies in supply chains are unaware of a serious bottleneck in a supply network, there is a greater chance that the network cannot respond to the disruption quickly. The third is *design information substitutability***.** If a product uses a specific design for a particular product, especially when the supplier uniquely controls design resources and processing of the product, then in a crisis, such products will be extremely difficult to replace by switching suppliers or processors. Finally, the study uses the perspective of *design information portability***,** which determines whether the design information used at a certain

[9] Hofman and Aronow (2012) uses three-year average of return on asset (ROA) and revenue growth and standard deviations of these two financial indicators to calculate resiliency of supply chains.

manufacturing plant can be transferred to another plant should a crisis arise. This, if each node in a supply chain possesses design information portability, it will contribute to the resiliency of the supply chain.

These concepts are corroborated by much of the empirical research. For example, through the case study and phone interview with the executives, Blackhurst, Craighead, Elkins, and Handfield (2005) found that the executives considered visibility as a key issue related to dealing with disruptions, particularly in trying to discover disruption. After collecting questionnaires from 760 executives from firms operating in Germany, Wagner and Bode (2006) estimated ordinary least square regression models. They revealed that supply chain characteristics such as a dependence on certain customers and suppliers, the degree of single sourcing or dependence on global sourcing are positively correlated to a firm's exposure to supply chain risk. They also found the unexpected result that dependencies on suppliers would decrease the exposure to natural hazard risks. They attributed this result to the fact that Germany is less vulnerable to natural hazards and suggested that future study must investigate the relationship between a firm's reliance on a supplier and exposure to catastrophe risks. From this perspective, Thailand's 2011 floods also provide a valuable insight.

# Section I: Case Study of Thailand's Floods of 2011

## 6.3. Overview of the Thailand's Flood in Fall 2011

### 6.3.1. Contributing Factors to Floods

The Thailand flood impacts resulted from both natural and human-made factors. The first factor was a "La Ninã" event that increased rainfall by 143% in the northern regions of Thailand early in the monsoon season, which consequently doubled runoff (Komori et al., 2012; Ziegler, Lim, Jachowski, & Wasson, 2012). Due to this heavy rainfall, reservoirs exceeded their threshold storage level to prevent floods by the time large tropical storms such as Nock-Ten and Muifa arrived in late July 2011 (Ziegler et al., 2012). In particular, the north-central region of Thailand had 40% above normal precipitation in September, and this represented the seventh straight month of above-normal rainfall levels (Sousounis, 2012).

The second factor was the topological aspects of the region. Due to the gentle slope of the downstream parts of the Nan and Yom Rivers, which consist of the upstream of the Chao Phraya River system, a large area was flooded, and a high volume of discharge flowed into the lower watershed from the narrow section of the river system (Komori et al., 2012). In addition, the Chao Phraya River has the only modest bank full capacity, particularly in the downstream section, which is flood prone. Thus, there was much more water upstream than the downstream channel was able to manage (The World Bank, 2012). Then, the water that flowed into the lower watershed broke water gates and levees downstream from the Chao Phraya River (Komori et al., 2012).

The third factor was the land-use of the region. Bangkok is located on former floodplains, where natural waterways and wetlands were replaced with urban structures (Engkagul, 1993). Although Bangkok and surrounding industrial parks are located in flood-prone areas, developers have failed to prepare for the strong likelihood of persistent and recurrent flooding (Ziegler et al., 2012). In addition, land subsidence in Bangkok might have worsened floods' damage, given that the elevation of Bangkok is 0.5 meter to 1.5 meter above mean sea level (Asian Development Bank, 1994). Land subsidence in Bangkok was 10cm per year in 1978, though the rate declined to 0.97 cm per year between 2002 and 2007 (The World Bank, 2010). Cumulative subsidence is reported by several studies. Nutalaya, Yong, Chumnankit, and Buapeng (1996) reported that it was 160 centimeter between 1933-1988 while Ramnarong (1999) found that it was 54 centimeter between 1978 and 1982. Consequently, many areas in the city are vulnerable to persistent flooding even if the water conveyed over the levees or through levee breach is modest.

The fourth factor was the water management in the region. There are two competing objectives that confound water management: (i) storing water for use during the dry season; and (ii) minimizing flooding during the wet season (Lebel, Manuta, & Garden, 2011). In addition, Thailand has had to adapt to rapid changes in water use as a result of the country's swift evolution from an agricultural to an industrial nation. Due to the urbanization and decentralization of Thailand, it has also become difficult to secure floodplains (METI, 2012). Poor governance and coordination of the national and local governments have also made it difficult to control floods as a whole (METI, 2012). The floods were not individually extreme events in terms of the return period of the peak flow. However, the duration of flooding was extreme, and the recurrent input of water overwhelmed the storage capacity of the reservoirs and the bank capacity of the rivers, following the existing reservoir operation policy. If the reservoirs had been drained or lowered in anticipation of the floods, some of the damage could have been avoided. However, if the floods had not materialized subsequently, regional water supply would have been adversely impacted. As it turned out the reservoirs were filled by the first flood wave and given the subsequent rainfall maintaining rivers below the bank full capacity was not feasible. The situation could have been averted or the impact reduced if accurate climate forecasts were available. Consequently, a combination of management and physical constraints conspired to create the flood impacts.

### 6.3.2. Physical Damage

The flood in Thailand that occurred in fall 2011 is the most notable example showing the impact of floods both on industries and the whole economy. The floods began in the summer of 2010 and gradually subsided by the end of the year. According to Department of Disaster Prevention and Mitigation, Ministry of Interior of Thailand, there were 1.8 million households affected, 813 casualties(Munich Re, 2012), and 17,578 square kilometers of inundated farm lands (Table 6-2).

Table 6-2: Impact of 2011 floods in Thailand

| | |
|---|---|
| Impacted Households [a] | 1,886,000 |
| Destroyed homes [b] | 19,000 homes |
| Displaced people [a] (Affected people) | 2.5 million people |
| Casualty | 813 people |
| Impacted farm land [a] | 17,578 square kilometers |
| Economic Damage and Losses [b] | Thai Baht 1.43 trillion (USD 46.5 billion) |
| in Manufacturing Sector | Thai Baht 1,007 billion (USD 32 billion) |

*Source*: [a] The Goverment of Thailand (2011) [b]The World Bank (2011)

## 6.4. Costs to the Whole Economy of Thailand

### 6.4.1. Loss of GDP

The impact of the prolonged floods on the world and the Thailand economy was devastating. UNISDR (2012) estimated that Thailand's 2011 flood reduced the world's industrial production by 2.5%. The World Bank (2012) estimated that the real GDP growth rate declined from 4.1% expected to 2.9%. The impact of the flooding in Thailand was obviously reflected in the insured damage, which has been assessed $10 billion (Figure 6-1) (Munich Re, 2012). The top three major non-life insurance companies in Japan paid out $5.3 billion for the damage caused by the flooding in Thailand, an amount that was greater than the one resulting from the earthquake and the tsunami on March 11, 2011(Fukase, 2012).

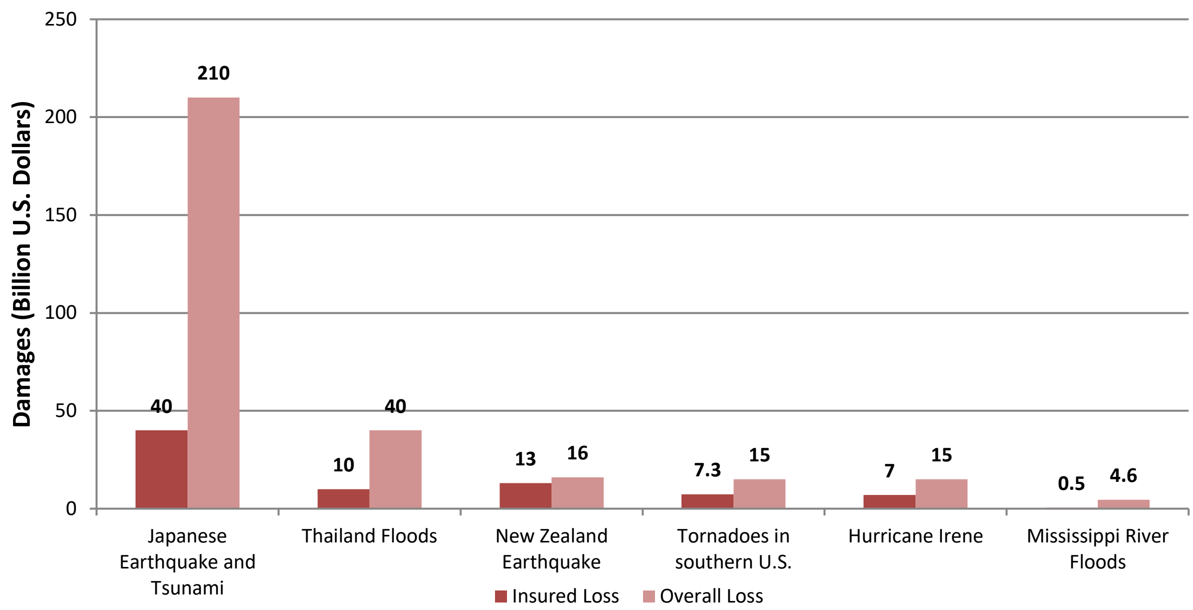



Figure 6-1: Damages of the major disasters in 2011. *Source*: Munich Re (2012)

### 6.4.2. Impact on Industrial Parks

In addition to affected farmland, seven industrial parks were inundated (Table 6-3). The total number of companies in the seven inundated industrial parks was 804. Of those, 56.7% were owned or operated by Japanese companies. It took from 33 to 62 days to complete discharging from the inundated industrial complexes (Table 6-3).

Table 6-3: List of flooded industrial parks

| Industrial Park or Estate | Province | Number of companies (number of Japanese companies) | Inundated date | Date completed draining water | Time to finish drainage (days) |
|---|---|---|---|---|---|
| Saha Ratta Nanakorn Industrial Estate | Ayutthaya | 42 (35) | Oct. 4, 2011 | Dec. 4, 2011 | 62 |
| Rojana Industrial Park | Ayutthaya | 218 (147) | Oct. 9, 2011 | Nov. 28, 2011 | 51 |
| Hi-Tech Industrial Estate | Ayutthaya | 143 (about 100) | Oct. 13, 2011 | Nov. 25, 2011 | 44 |
| Bang Pa-in Industrial Estate | Ayutthaya | 84 (30) | Oct. 14, 2011 | Nov. 17, 2011 | 35 |
| Nava Nakorn Industrial Estate | Pathum Thani | 190 (104) | Oct. 17, 2011 | Dec. 8, 2011 | 53 |
| Bankadi Industrial Park | Pathum Thani | 34 (28) | Oct. 20, 2011 | Dec. 4, 2011 | 46 |
| Factory Land (Wangnoi) Industrial Park | Ayutthaya | 93 (7) | Oct. 15, 2011 | Nov. 16, 2011 | 33 |
| Total | | 804 (451) | | | |

*Source*: JETRO (2011). Adapted from Haraguchi et al (2015)

Table 6-4 originally reported by Sukegawa (2012)[10] shows what percentage of facilities in these inundated industrial parks restored operations. 75 % of factories in the seven inundated industrial parks have resumed operations, including resumption of operations in part, as of June 1, 2012. However, only 40% of those factories have recovered to pre-flood levels of production. Therefore, some 17.5 % of factories located in the seven inundated industrial parks could not resume operations. Saha Ratta Nanakorn Industrial Estate, which was the first one inundated, has the lowest percentage, 59%, of restoration, while the first three industrial parks inundated have the highest percentages of closing businesses (11% for Saha Ratta Nanakorn Industrial Estate and Hi-Tech Industrial Estate, and 14% for Rojana Industrial Park).

Table 6-4: Status of recovery of inundated industrial parks as of June 1, 2012.

| Industrial park or estate | Number of factories | Operation has restored | | | Operation has not restored yet | | Businesses has closed | |
|---|---|---|---|---|---|---|---|---|
| | | Fully Restored | Partly Restored | % | | | | |
| Saha Ratta Nanakorn Industrial Estate | 46 | 14 | 13 | 59 | 14 | 30% | 5 | 11% |
| Rojana Industrial Park | 213 | 69 | 85 | 72 | 30 | 14% | 29 | 14% |
| Hi-Tech Industrial Estate | 143 | 75 | 27 | 71 | 25 | 17% | 16 | 11% |
| Bang Pa-in Industrial Estate | 90 | 46 | 31 | 86 | 12 | 13% | 1 | 1% |
| Nava Nakorn Industrial Estate | 227 | 55 | 107 | 71 | 57 | 25% | 8 | 4% |
| Bankadi Industrial Park | 36 | 7 | 17 | 67 | 9 | 25% | 3 | 8% |
| Factory Land (Wangnoi) Industrial Park | 84 | 70 | 14 | 100 | 0 | 0% | 0 | 0% |

Source: Sukegawa (2012). Adapted from Haraguchi et al (2015).

## 6.5. Impacts on Industries and Firms

### 6.5.1. Overview of Affected Industries

Due to the damage to these industrial parks, the manufacturing sector contributed to 8.6% of the decline of the real GDP between October and December 2011 (METI, 2012). The manufacturing industry comprised 39.0% of Thailand's GDP in 2011, and the damage to the manufacturing sector was 122 billion baht, which represented 71% of the total loss of real GDP (171 billion baht) (Sittipunt, 2012). For this reason, the disruption of supply chains in the manufacturing sector had such a large influence on the Thai economy as a whole.

[10] Sukegawa [29] in Japan External Trade Organization (JETRO) inquired to Industrial Estate Authority of Thailand (IEAT). JETRO asked about the level of recovery of all of 839 factories in all of 7 inundated parks.

Specifically, according to METI (2012)[11], the following products in the manufacturing industry declined productions in November 2011: transport machinery industry (such as pickup truck and passenger car) was minus 84.0% , compared to the same month of the last year; office equipment (mainly HDD) was minus 77.2%; information and communications equipment (semiconductor devices, IC communication equipment, television, radio, TV etc.) was minus 73.0%, electrical products such as air conditioning, refrigerator was minus 58.7%. Therefore, this paper will focus on these two sectors: automobile and electronics sectors.

### 6.5.2. Automobile Sector

The Federation of Thai Industries reported that the total number of cars produced in 2011 was 1.45 million, which was 20% below the expected production number (1.8 million cars) at the beginning of 2011 (JETRO, 2012a). This number was down 11.4% when compared with the production of cars in 2010 (1.64 million cars), and experts attribute the decline to the supply chain disruption caused by the Japanese earthquake and the Thai floods. Particularly, the production from October 2011 to December 2011 declined drastically while the production in April and May 2011 decreased possibly due to the time-lagged effect of the Japanese earthquake and Tsunami in March 2011 (Figure 6-2).

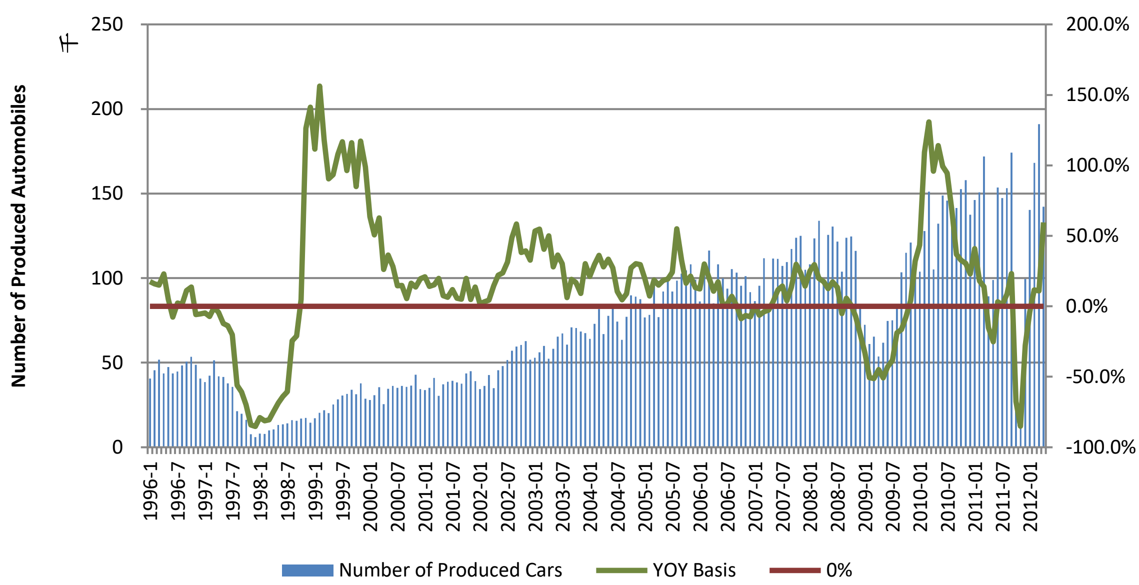



Figure 6-2: Monthly Production of Automobiles in Thailand (passenger + commercial cars)
*Source*: METI (2012)

[11] METI stands for Ministry of Economy, Trade, and Industry of Japanese government. 2012's White Paper on International Economy and Trade published by Ministry of Economy, Trade and Industry of Japanese government has featured Thailand floods of 2011 in one of their chapters.

## Direct and Indirect Damage to Japanese Automakers

Thailand is one of the production hubs for global automobile manufacturers, particularly for Japanese automakers. Japanese firms and their family companies account for approximately 90% of sales and exports of automobile in Thailand. Thus, this paper focuses on Japanese automakers to measure the impacts of floods on the automobile sector in Thailand. First, Honda Motor Company, Ltd. had to stop its operations beginning on October 4, 2011, at the Ayutthaya factory and beginning on October 6, 2011, at its factory near Bangkok. Specifically, the factory at Ayutthaya was inundated on October 8. As far as Toyota Motor Corporation Ltd. and Nissan Motor Company Ltd. are concerned, their factories were not inundated, but their operations were shuttered due to lack of parts from suppliers beginning on October 10, 2011, for Toyota, October 11 for Ford, and October 17, 2011, for Nissan.

## Needed Time to Recover

The time required to recover from the Thai floods, namely TTR, differed with each automaker and was largely dependent upon the extent of the damage suffered at the factories in question. Toyota required 42 days to resume operations; Nissan, on the other hand, resumed operations in just 29 days. In contrast, Honda, whose factory at Ayutthaya was inundated, required 174 days to resume its production cycle due to the extensive nature of the damage to its facility (Table 6-5).

Table 6-5: Damages of factories of Japanese automakers and required TTR.

| | Factory | Place | Damage | Starting date for adjusted/stopped production | Date when production is resumed | TTR (days) |
|---|---|---|---|---|---|---|
| **Honda** | Honda Automobile | Rojana Industrial Park | Factory was Inundated on Oct 8th 2011, and stopped the production. | Stopped production since 10/4/2011 | 3/26/2012 (Partly resumed) | 174 |
| **Honda** | Thailand Manufacturing Company Ltd | Bangkok | No inundation of factory. Stopped production due to the lack of parts supply. | Stopped production since 10/6/2011 | 11/14/2012 (Partly resumed) | 40 |
| **Honda** | Suzuka Factory | Japan | Adjusted production due to the lack of parts supply. | Adjusted production since 11/7/2011 | 12/5/2011 (Normal level of production) | 28 |
| **Honda** | Saitama Factory | Japan | Adjusted production due to the lack of parts supply. | Adjusted production since 11/17/2011 | 12/5/2011 (Normal level of production) | 18 |
| **Honda** | 6 Factories in the north America | North America | Adjusted production due to the lack of parts supply. | Adjusted production since 11/2/2011 | 12/1/2011 (Normal level of production) | 30 |
| **Honda** | Malaysia | Malaysia | Stopped production due to the lack of parts supply. | Stopped production 10/25/2011 | not available | Not available |
| **Toyota** | Toyota Motor Thailand Ltd, Samrong Assembly | Samut prakan Province, Thailand | No inundation of factories. Stopped production due to the lack of parts supply. | Stopped Production since 10/10/2012 | 11/21/2011 (Partly resumed) | 42 |
| **Toyota** | Toyota Motor Thailand Ltd, Gateway Assembly | Chachoengsao Province | No inundation of factories. Stopped production due to the lack of parts supply. | Stopped Production since 10/10/2013 | 11/21/2011 (Partly resumed) | 42 |
| **Toyota** | Toyota Motor Thailand Ltd, Baan Poe Assembly Plant | Chachoengsao Province | No inundation of factories. Stopped production due to the lack of parts supply. | Stopped Production since 10/10/2014 | 11/21/2011 (Partly resumed) | 42 |
| **Nissan** | Nissan Thailand, HQ Assembly Plant | Samut Prakan Province | No inundation of factories. Stopped production due to the lack of parts supply. | Stopped production since 10/17/2012 | 11/14/2011 (Partly Resumed) | 29 |
| **Nissan** | Siam Motors and Nissan HQ Assembly Plant | Samut Prakan Province | No inundation of factories. Stopped production due to the lack of parts supply. | Stopped Production Since 10/17/2012 | 11/14/2011 | not available |

Source: Press release of each company. Adapted from Haraguchi et al (2015)

### *Consequences and Impact*

The impacts vary by company. Toyota lost more cars to the Thai floods than to the Japanese tsunami. Toyota, Honda, and Nissan lost 240,000, 150,000, and 33,000 cars, respectively, because of the Thai floods (Table 6-6). Toyota and Honda were more impacted by the flood than Nissan; and Nissan recovered more quickly than other auto companies because it had dissolved the KEIRETU system[12], diversified sources of supply, and globalized the procurement system (Kushima, 2012). Also, Nissan had a higher inventory to prepare for increasing sales. In contrast to Nissan, whose plants were not inundated, Toyota lost the almost same amount of operating profit as Honda even though Toyota's three assembly plants were not inundated and Honda's plants were (Table 6-5, Table 6-6)._This shows that supply chain characteristics, for example, the damage to critical node such as an assembly plant, inventory management, and the degree of a firm's reliance on suppliers, translates into damages across supply networks.

[12] A Keiretsu is a group of closely related family companies, often with interlocking ownership.

Table 6-6: Impacts of the Thailand floods on Japanese major automakers

| Statistics | Toyota | Honda | Nissan |
|---|---|---|---|
| Number of lost cars at global due to Thailand floods (thousand cars) | 240 | 150 | 33 |
| Operating profit (billion yen) | 270 ($3.4B)[a] | 200 ($2.5B) | 510 ($6.4B) |
| Lost operating profit due to Thailand floods (billion yen) | 100 ($1.25B) | 110 ($1.4B) | 5.9 ($0.07B) |
| Percentage of loss of operating profit caused by Thailand flood to operating profit | 37.04% | 55.00% | 1.16% |
| Operating Profit (% compared to 2020) | -42.30% | -64.90% | -4.70% |
| Net profit (billion yen) | 200 ($2.5B) | 215 ($2.7B) | 290 ($3.6) |
| Net profit (% compared to 2010) | -57.50% | -59.70% | -9% |

[a] *The exchange rate was used for 80 Japanese yen for 1 U.S. dollars, which was the rate at that time.*
*Source*: Press release of each companies

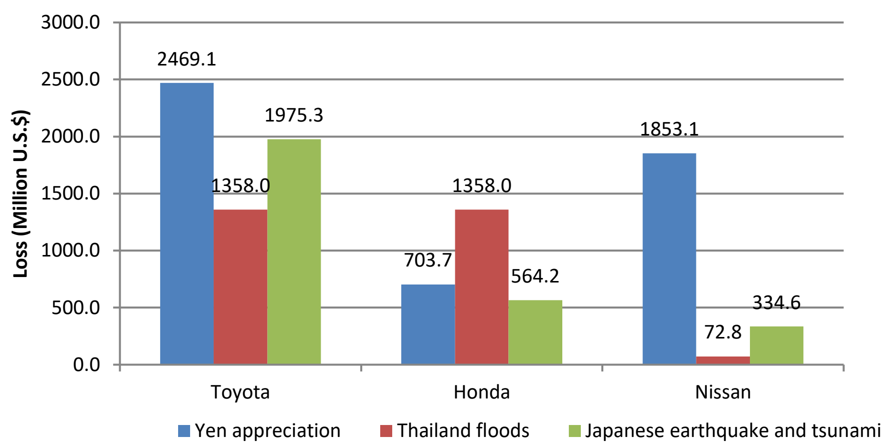



Figure 6-3: Decreased operating profits of Japanese major automakers (April – December 2011). *Source*: Press releases of each company.

In order to show the interdependencies of automobile sectors among countries, the study referred to the Intermediate goods trade of transportation machinery between Thailand and other countries. Table 6-7 shows that the exports from Thailand are more important for the Philippines (14.30%), Malaysia (26.00%), and Indonesia (25.80%) than for Japan (8.0%) and NAFTA (0.30%). Therefore, this study looked at Malaysia and Indonesia to examine the indirect effects of the flooding in Thailand to the supply chains.

Table 6-7: Trade of intermediate goods of transportation machinery of Thailand in 2010

| | | Export from Thailand | Import to Thailand |
|---|---|---|---|
| **NAFTA** | | 306 | 156 |
| | | 0.30% | 0.20% |
| **Taiwan** | | 71 | 124 |
| | | 2.70% | 2.20% |
| **South Korea** | | 29 | 190 |
| | | 0.60% | 1.60% |
| **Japan** | | 603 | 3770 |
| | | 8.00% | 9.0% |
| **China** | | 57 | 269 |
| | | 0.30% | 1.30% |
| **Philippines** | | 103 | 361 |
| | | **14.30%** | **42.30%** |
| **Malaysia** | | 685 | 101 |
| | | **26.00%** | 6.80% |
| **Indonesia** | | 792 | 282 |
| | | **25.80%** | **20.00%** |

Upper cell is amount ($1 million) and lower cell is share in the exports/imports of a partner country (%). Total amount of exports is $4.1 billion and that of imports is $ 6.0 billion. *Source*: METI (2012)

The decrease in production impacted the sales for the trade partners to which manufactured cars in Thailand are exported. Figure 6-4 and Table 6-8 show how Thailand's year-over-year (YOY) basis of automobile production is associated with those of Malaysia and Indonesia. Indonesia's YOY basis is robust, while Malaysia experienced a decrease in automobile production between October 2011 and January 2012, when Thailand was experiencing supply chain disruptions. However, after February 2012, when Thailand resumed production, Malaysia seemed to need even more time to resume sales.

Table 6-8: Automobile production (Number of cars on YOY basis)

| | Thailand | Indonesia | Malaysia |
|---|---|---|---|
| Jan-11 | 40.81% | 41.96% | 17.42% |
| Feb-11 | 17.91% | 31.05% | 1.55% |
| Mar-11 | 13.72% | 29.56% | 3.00% |
| Apr-11 | **-15.16%** | **-8.30%** | **-24.66%** |
| May-11 | **-25.24%** | **-1.99%** | **-20.34%** |
| Jun-11 | 3.20% | **-1.75%** | **-18.04%** |
| Jul-11 | 1.01% | 22.38% | **-7.85%** |
| Aug-11 | 8.60% | 13.40% | **-11.93%** |
| Sep-11 | 23.13% | 74.42% | 29.46% |
| Oct-11 | **-67.62%** | 22.33% | **-5.49%** |
| Nov-11 | **-84.92%** | 0.53% | **-2.51%** |
| Dec-11 | **-27.64%** | 28.62% | **-22.85%** |
| Jan-12 | **-3.90%** | **-1.40%** | **-14.67%** |
| Feb-12 | 11.51% | 45.57% | 7.48% |
| Mar-12 | 10.89% | 25.89% | **-12.27%** |
| Apr-12 | 62.80% | 49.53% | 19.80% |
| May-12 | 110.52% | 28.48% | 18.95% |
| Jun-12 | 35.87% | 12.74% | 14.67% |
| Jul-12 | 46.25% | **-7.13%** | 0.44% |
| Aug-12 | 39.96% | **-4.04%** | **-12.15%** |
| Sep-12 | 33.52% | **-6.78%** | 11.88% |
| Oct-12 | 410.05% | **-5.24%** | 5.03% |
| Nov-12 | 982.85% | 48.92% | 32.85% |
| Dec-12 | 122.63% | 20.72% | 40.95% |

Bold numbers are months of negative YOY Basis.
*Source*: Markline

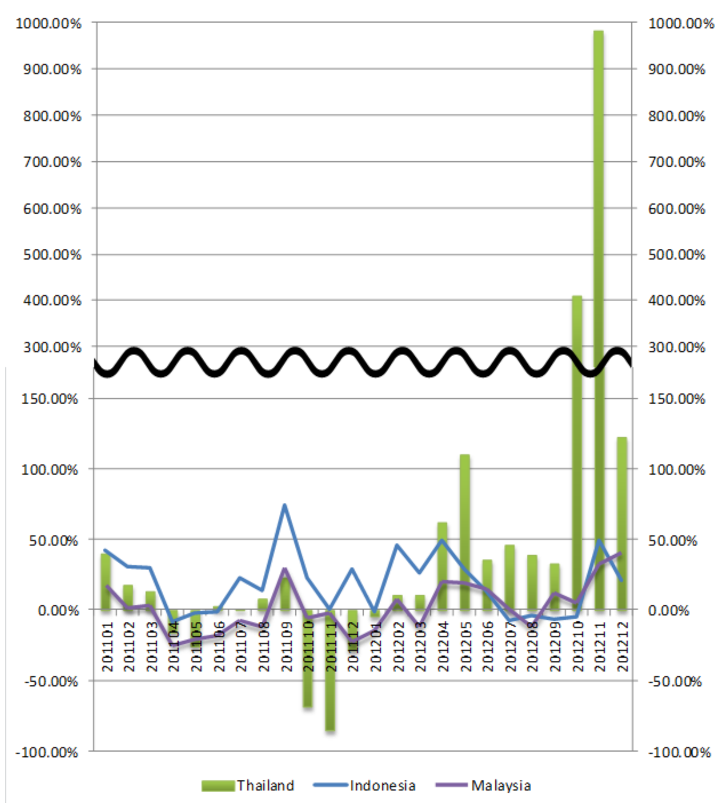



Figure 6-4. Production of automobiles in Thailand, Indonesia, and Malaysia on YOY basis. *Source*: Markline

Figure 6-5 demonstrates how the reduced production of automobiles in Thailand influenced the consumption of automobiles in Malaysia and Indonesia. Malaysia's sales of automobiles decreased, up to a minus 25%, until April 2012. Indonesia's consumption was relatively robust; however, consumption in November 2011 became negative even though Indonesia was experiencing a constant increase in sales in most of the previous months.

In addition, between January 2011 and November 2011, the import of transport equipment in the Philippines from Thailand declined by 21.5% compared to the same period in 2010 (automobiles' decline rate was 36.9% and automobile parts' decline rate was 35.1%), while the total import in the Philippines from Thailand decreased by 8.3% (Kamata, 2012). As a result of the lack of import from Thailand, the sales of new automobiles in the Philippines decreased by 4.0%, up to 140,000 cars (Kamata, 2012). This example shows that the impact of supply chain disruption will resonate to overseas' markets through global supply chains.

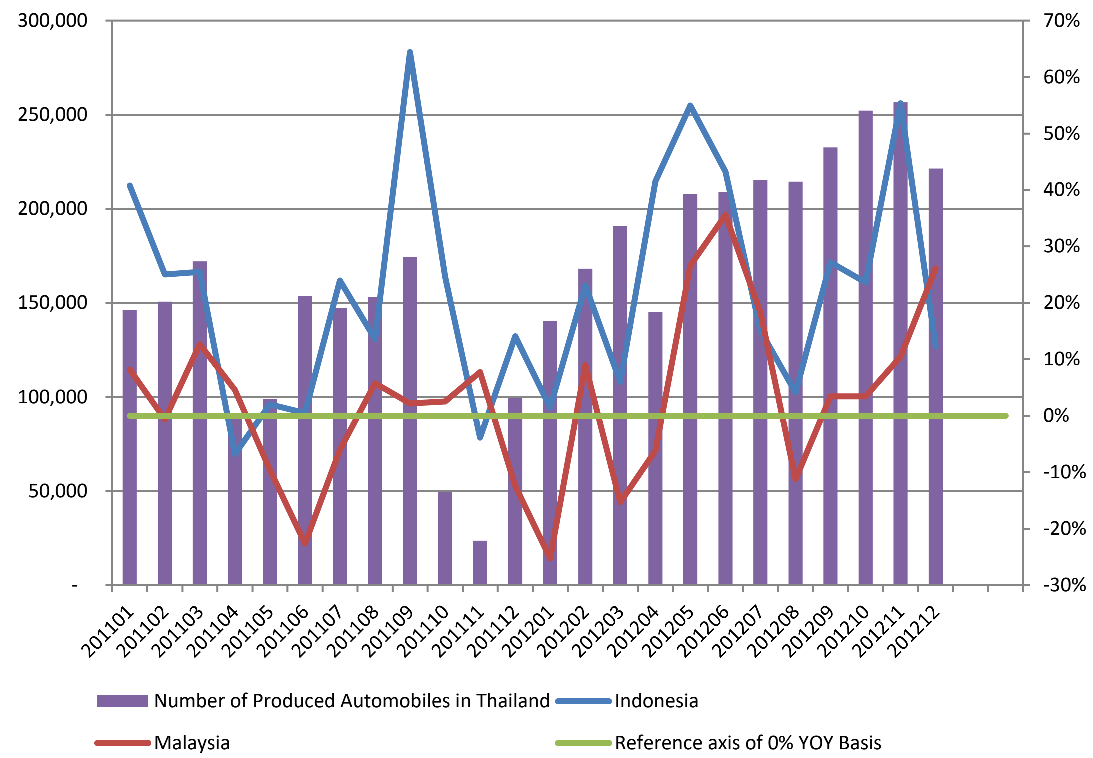



Figure 6-5: Number of produced automobiles in Thailand and YOY Basis of number of sold automobiles in Malaysia and Indonesia

### *Cause of the Damage*

An analysis by METI (2012) concluded that the automobile sector suffered these enormous losses primarily because one company, that produces critical components for automobile makers, was inundated. The manufacturer in question produces components such as power integrated circuits (IC); system LSIs for audio and navigation; transistors; and condensers. Although METI (2012) did not specify the name of the company, it is very likely ROHM Co., Ltd., a major producer of ICs and other electronic components. It has been reported that one of its competitors, Renesas Electronics Corporation, alternatively produced for ROHM. METI (2012) claims that due to the dearth of electronics components as a direct result of the flooding, automobile sectors were indirectly impacted, and in particular passenger vehicles that routinely include such electronics equipment in their design. The second reason the damage to the automobile industry was so great was the location of facilities and factories. METI (2012) and Ishii(2006) both argue that transportation costs were the primary factor in these automakers' decisions to invest in these Thai locations, which are close to ports, and that it is normal for the industry to select such a location since automobiles are both large and heavy, representing substantial shipping costs.

### 6.5.3. Electronics Sector

This section will examine mainly the impacts of floods on Hard Disk Drive (HDD) makers.

#### *Direct and Indirect Damage to HDD makers*

The electronics sector was also severely impacted. Before the 2011 floods, Thailand produced approximately 43% of the world's hard disk drives (METI, 2012). Western Digital Corporation, which produced one-third of the world's hard disks, lost 45% of its shipments because their factory in Bang Pa-in Industrial Estate, Ayutthaya was inundated (Tibken, 2012). The Toshiba factory, one of the four major makers of HDD, was also inundated. Toshiba was able to execute alternate production in the Philippines. While factories of Samsung and Seagate Technology, other two makers of the four major manufactures, were not inundated, they were forced to reduce production due to the lack of parts from suppliers who were impacted.

#### *Needed Time to Recover*

Table 6-9 shows the damages and needed TTR of major makers of HDD in the world. Western Digital partly restored the production after 46 days of stoppage. Toshiba, which has factory in Nava Nakorn Industrial Estate, needed 114 days to restore operations.

Table 6-9: Damages to major HDD makers.

| Company | Place of Factories | Damage | State of Operation /Production |
|---|---|---|---|
| **Western Digital** | 1) Bang Pa-in Industrial Estate<br>2) Nava Nakorn Industrial Estate | Factories inundated (2m) | - Stopped production since Oct 16, 2011<br>- Partly restored on Nov 30, 2011<br>- Needed days to restore:46 days |
| **Toshiba** | Nava Nakorn Industrial Estate | Factory was inundated (1m) | - Stopped production since Oct 11, 2011<br>- Alternate production in Philippines<br>- Partly restored Thai factory on Feb 1, 2012<br>- Need dates to restore: 114 days |
| **Seagate Technology** | 1) Seagate Teparuk, Amphur Muang, Samutprakarn Province<br>2) Seagate Korat, Amphur Sungnoen, Nakhon-Ratchasima | Factories were not inundated | - Some adjusted production due to the lack of supply from suppliers |
| **Samsung** | In South Korea | Factories were not inundated | - Some adjusted production due to the lack of supply from suppliers |

*Source*: Press release

## Consequences and Impacts

HDD shipments from the industry's five major manufacturers declined severely in the fourth quarter of 2011 to 123.3 million units, which was down 30% from 175.2 million units the quarter before (Zhang, 2012). The effect of the lost electronic parts production rippled across the global economy. The lack of hard disk drives increased the price of desktop HDD by 80%-190% and mobile HDD by 80-150%. This clearly shows that the world economy is closely interconnected through a global supply chain network and the indirect damage of disasters now easily affects the consumer market at the global scale in the electronics sector.

In terms of the impact on the market price, even six months after all the inundated industrial parks completed water drainage after the flooding, most of the prices of both hard disk drives (HDD) and solid state disks(SSD) remain higher than the prices before the floods (Hruska, 2012)(Figure 6-6)

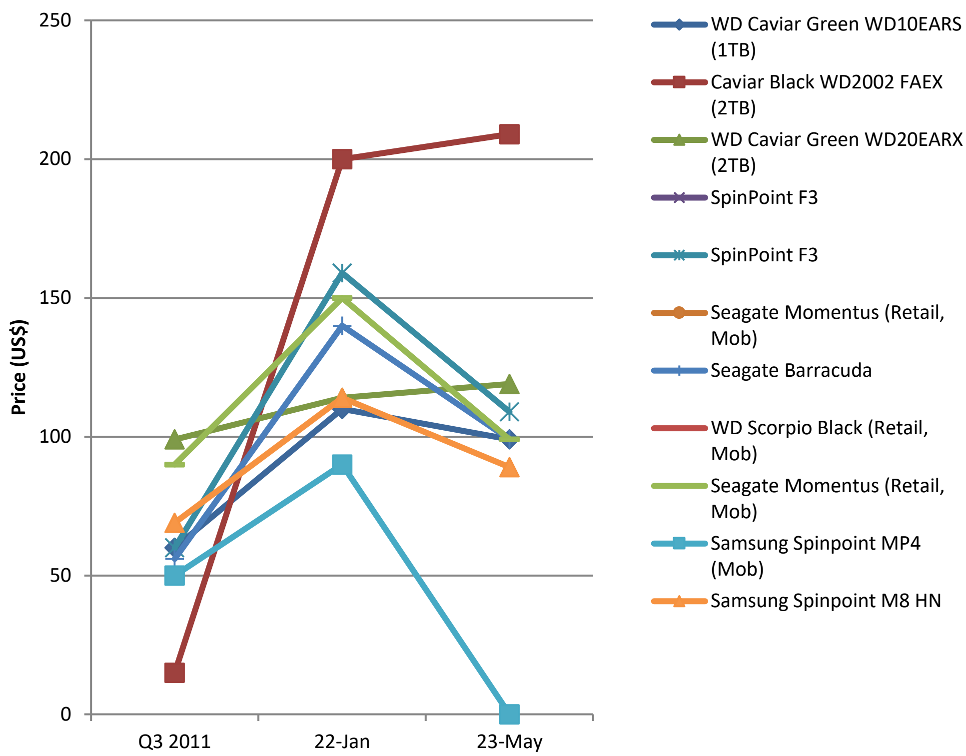



Figure 6-6: Change of Prices of HDD and SSD. *Source*: Hruska [36]

### *Differences in Electronics Industry*

Another example illustrating that the impact of floods was distinct among companies in the same industry is shown in the electronics sector. In the beginning of 2012, Western Digital's earnings decreased 35%, up to 145 million dollars, while Seagate increased its profit from 150 million dollars to 563 million dollars. This is primarily because Western Digital's factories were in the flood zones, while Seagate was mainly affected through their supply chain (Vilches, 2012).  As a consequence, Seagate recaptured the top position in hard disk drive shipments during the fourth quarter of 2011, since it only declined 8% compared to third-quarter figures of 50.8 million units. Western Digital's shipment, on the other hand, declined significantly by 51%, from 57.8 million units in the earlier quarter (Zhang, 2012).  Thus, the causes for these differences must be investigated in the future study.

### 6.5.4. Difference Between Automobile and Electronics Sectors

The production recovery of HDD makers was slower than that for automobiles. Figure 6-7 shows that the transport equipment industry's index was higher than the same months in the last year while HDD sectors were still lower. Many companies in the electronics industry had facilities in Ayutthaya, where industrial parks were inundated. In contrast, some automobile manufacturers had recently acquired facilities in regions southeast of Bangkok, such as Chonburi and Rayong Province, where only some companies were inundated. On the other hand, METI (2012) described the different responses among these two sectors in terms of alternate production. Major producers of HDD and electronic component parts fully operated their facilities in countries other than Thailand for alternative production. However, automobile companies could not transfer their production to other areas. In this sense, the design information portability of the automobile sector was lower than that of the electronic sector.

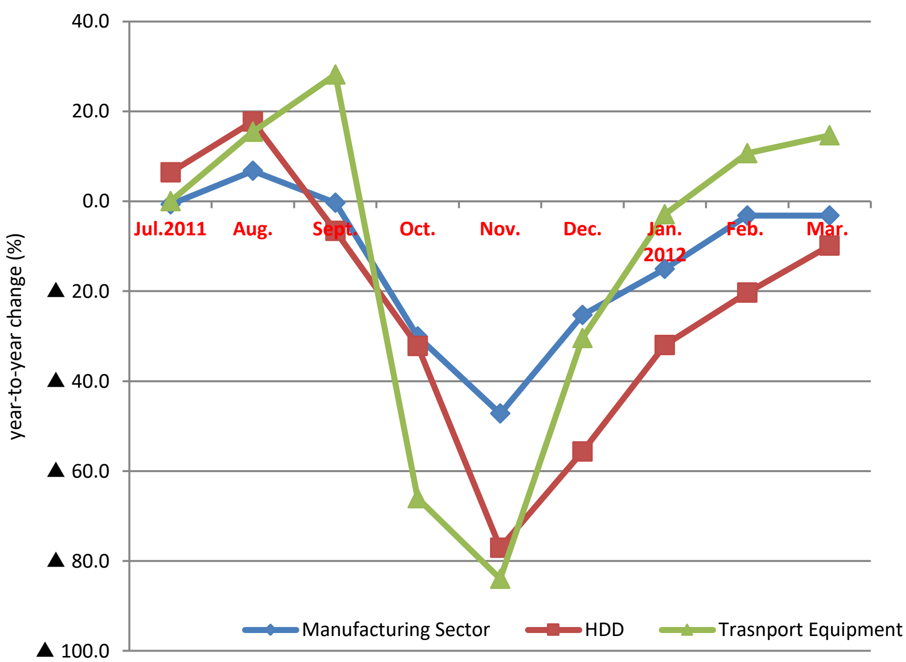



Figure 6-7: Production index of manufacturing, HDD and transport machinery. *Source*: The Office of Industrial Economy through METI (2012)

## 6.6. Recovery and New Responses

### 6.6.1. Importance of the Issues and Ignorance among Some Companies

Interestingly, existing surveys demonstrate that many companies will not significantly change their investment behavior. According to a survey conducted by Japan External Trade Organization(JETRO)[13],

[13] JETRO conducted the survey on January 11 of 2012 to 95 companies. 50 companies (40 manufactures and 8 non-manufactures) were directly impacted. 45 companies (33 manufactures and 12 non-manufactures) were indirectly impacted.

78% of 50 companies directly impacted by the floods continued to operate in the same location (JETRO, 2012b). The survey also concluded that some of these companies could not transfer to different facilities due to a lack of financial capacity. In comparison, 16 % moved their operations to places other than the original inundated industrial complexes (JETRO, 2012b). This is consistent with the results of a survey conducted by METI (2011).[14] Of 67 surveyed companies, some 68% responded that they would not change their plans for investment in plant and equipment in fisical year (FY) 2011 as a result of the business impact of the floods in Thailand (Figure 6-8). Additionally, of 62 Japanese companies surveyed, 66% answered that Thailand still represented an appealing investment (Figure 6-9). This is because companies might have stronger incentives to invest to Thailand since Japan and Thailand have had a free trade agreement since 2007.

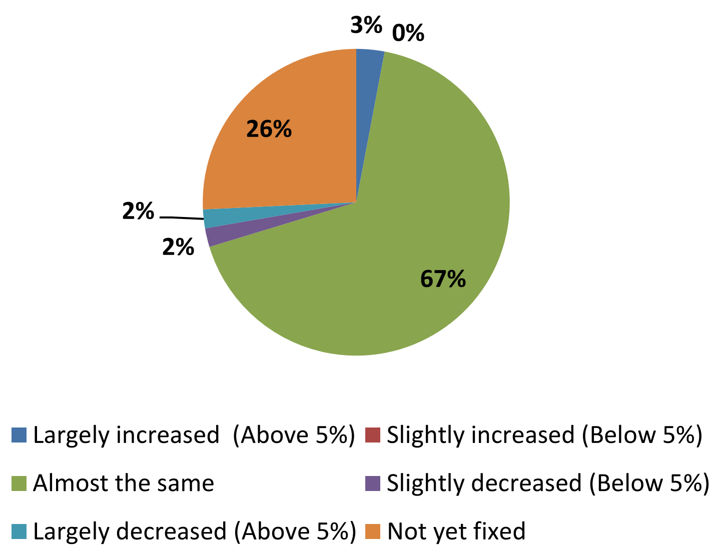



Figure 6-8: Change in FY 2011 equipment investment plan under the impact of the flood in Thailand. The number of Japanese companies that responded is 65. *Source*: METI (2011)

[14] METI conducted the survey from November 30, 2011 to December 7, 2011 to 67 large companies (including 59 manufacturers and 8 non-manufacturers).

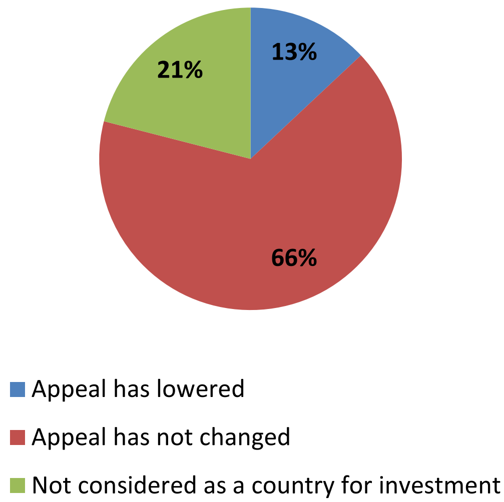



Figure 6-9: Change in appeal of Thailand as the country for investment after the flood. The total number of Japanese companies that responded is 62. *Source*: METI (2011)

However, the METI (2011) survey also revealed changes in attitudes regarding the need for alternative procurement sources. In Thailand, of 17 companies surveyed, a mere 24% indicated that they would replace all of their substitute suppliers with their original suppliers once the original suppliers recovered from the floods (Figure 6-10). In Japan and other affected countries, only a few companies (below 10% of 52 firms surveyed) answered that they would replace all of their substitute suppliers with their original suppliers, and approximately 20% of 52 companies in Japan and other countries answered that they would resume less than half of their business with their original suppliers (Figure 6-10). This demonstrates that there is a very real risk of suppliers losing customers, and that they must seriously consider flood risks in their investment decisions.

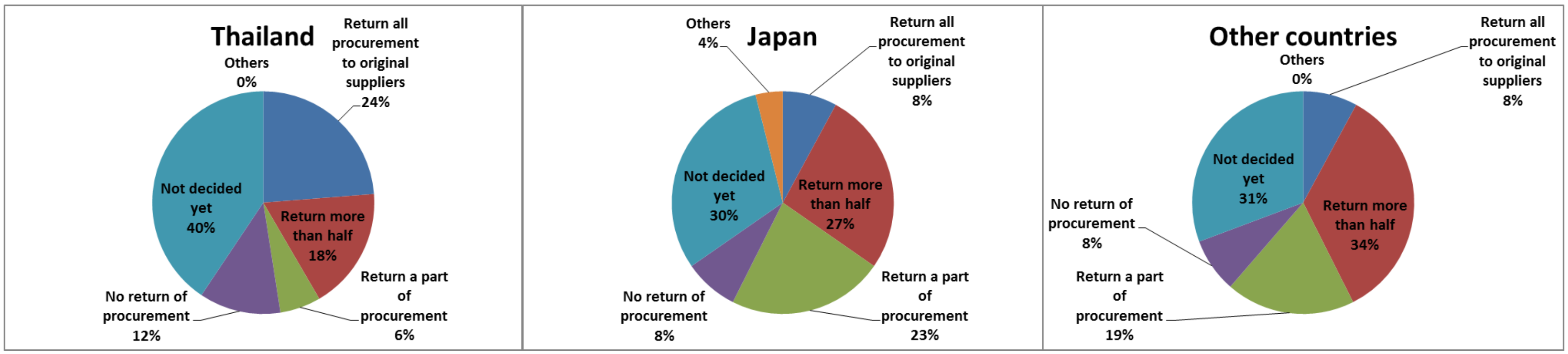



Figure 6-10: Substitution procurement period and prospect for substituting suppliers in Thailand, Japan and other countries. The total numbers of manufacturing companies that responded are 17, 26, and 26 respectively. *Source*: METI (2011)

### 6.6.2. Responses in Automobile and Electronics Industries

Some of the companies have already started redesigning the supply chain network. Toyota has reported that they are going to move some of the production in Japan to different regions, such as to the US, in order to change their globally centralized production system to a regionally independent production system, such as General Motors has already done. Takahashi (2012) also reported that Toyota requested that about 500 of their suppliers disclose details of their supply chains. After receiving responses from about half of them, they found that 300 production places could be vulnerable to risks. Then, Toyota requested that these suppliers mitigate risks by measures such as diversifying procurement, securing alternate facilities, and increasing inventories. At the same time, Toyota expects that suppliers will benefit, since they are trying to reduce the number of types of parts and increase the lot size of order from each supplier. In June 2013, Honda also started constructing its new automobile production plant in Prachinburi Province, which faces less flood risks since it is located in the higher elevation.

Also In the electronics industry, Kaga Electronics decided to close their factory in Rojana Industrial Park in Ayutthaya, which was inundated by the flood, and move to Amata Nakorn Industrial Estate, which is less vulnerable to flood risks. According to the METI that collected a survey from 67 companies from 13 industries operating in Thailand, 44% of the respondents were considering moving their production system (METI, 2011). Therefore, it is critical for local governments to properly manage floods since they will lose important economic advantages if many companies move their production hubs to safer areas.

### 6.6.3. Responses in Insurance Industry

The flood in Thailand has shown the insurance industry the importance of the supply chain for them, as well. For instance, Swiss Reinsurance Company Ltd expected the amount of its exposure from the flood would be approximately $600 million for their company and $10 billion to the entire industry, while Munich Reinsurance Company estimated its losses at approximately $655 million (Munich Re, 2012; Wright, 2012). It required some time before the total effect of insured damages was confirmed. This was partly because of the limited ability of survey companies to evaluate business interruption losses, such as lost revenue, especially in association with supply chains, because of the lag time to resume operating machinery, and retooling and rehiring of staff (Wright, 2012).

In Thailand, fire and profit insurance covered flood risks before 2011, while in other countries such as Japan, fire insurance does not cover flood risks. This increased the insured losses in Thailand drastically. Yet, after the floods in 2011, major insurers began executing sub-limits for flood coverage. Responding to this, the Thai government established the National Catastrophe Insurance Fund of Thailand (NCIF) in March 2012. Based on this fund, a Catastrophe Insurance Policy (CIP) was created in July 2012. Companies can apply for insurance that covers flood risks provided by CIP through private insurance companies.

### 6.6.4. Responses in the Government and International Society

In March 2012, the Thai government proposed strategies and action plans for flood prevention. These include local defense; industrial park protection; inner logistic roads; river dredging, dike and water gate; flood collection area and infrastructure strengthening; and forestation and dam management. The government also proposed action plans (Table 6-10).

Table 6-10: Proposed action plans by Mr. Chadchart Sittipunt, Deputy Minister of Transport, The Royal Thai Government

| | **Action Plan** | **Immediate (6months)** | **Medium (1 - 3 Years)** | **Long (3 - 5 Years)** |
|---|---|---|---|---|
| 1 | Dike in industrial Parks | x | | |
| 2 | King Dike | x | | |
| 3 | Dredging River Delta | x | | |
| 4 | Road Rehabilitation | x | | |
| 5 | Water Detention Area | x | x | |
| 6 | Raising Level of Highway | x | x | |
| 7 | River/Canal Dredging | x | x | |
| 8 | Upgrading Logistic Routes | x | x | x |
| 9 | New Dam and Reservoir | | x | x |
| 10 | New Flood Way | | | x |
| 11 | Single Command Center | x | x | |
| 12 | Forecasting and Warning Systems | x | x | |

*Source*: Sittipunt [30]

Foreign governments, particularly the Japanese government, have provided assistance to Thailand. The Japan International Cooperation Agency (JICA) completed the Flood Management Plan of the Chao Phraya River in July 2013 and provided technical assistance for a Single Command Authority of water management. In addition, the JICA continues to assist the Thai government with upgrading infrastructure such as major transportation routes and constructing new water gates that contribute to maintaining supply chains.

# Section II: Review of Methodologies and Potential Research Questions

## 6.7. Literature Review of Papers That Study the Supply Chain Disruptions

There are essentially three existing approaches to examining the impact of disasters on supply chains. The first, known as Input-Output Analysis, examines a model of all exchanges between sectors of an economy based on the relations of production. Conventionally, many studies rely upon this method since it is relatively simple and economical to develop models. This method can also examine economic interdependencies among various sectors and countries or targeted regions. Thus, I–O models can demonstrate indirect damage to industries resulting from interdependencies (MacKenzie, Santos, & Barker, 2012). I–O analysis examines not only negative impacts, but also positive impacts of a disruption (MacKenzie et al., 2012). Rose and Huyck (2016) point out the limitations of this approach. For example, it typically assumes linearity, which leads to a lack of understanding of behavioral context and market considerations. In terms of resiliency, I–O cannot incorporate adaptive resilience.

Another approach is Computational General Equilibrium (CGE), which is a multi-market model describing how individual businesses and households respond to price signals and external shocks, within the limits of available capital, labor, and natural resources (Dixon & Rimmer, 2002). The advantage of this approach is that the model can take into consideration behavioral context and can also assume nonlinearities and utilize prices and markets (Rose & Huyck, 2016). The limitation of this approach is that it is "complicated by data requirements (Rose & Huyck, 2016)." Both the I–O and the CGE approach fail to compare the features of different supply networks in terms of their structure, design, and topology.

The alternative to these two approaches is Network Analysis—there are several advantages to this type of analysis. For example, it can compare features among different supply chains. It can also enhance the visibility of supply chains when network analysis is applied. There are several areas of this field of analysis. The first example is neural networks. Neural networks are flexible and can be adjusted to new risk scenarios; as such, neural networks are very well-suited for complex information processing and analysis (Teuteberg, 2008). One potential disadvantage of neural networks is that too many nodes may lead to over-fitting, while too few nodes reduce classification accuracy (Teuteberg, 2008). Using the complex adaptive system (CAS), the model can be dynamic and evolve over time through interactions among agents (Pathak, Day, Nair, Sawaya, & Kristal, 2007). In contrast, CAS may fail to account for the internal interactions between mechanisms (Pathak et al., 2007). In order to capture the dynamics of supply chain networks and propose optimal network design, network analysis would be an appropriate method since the analysis can also differentiate various supply chains. Neural networks are actually one way of estimation or inference on causal networks. A more general framework is available through Bayesian Networks (Jensen & Nielsen, 2007; Pearl, 1988). Bayesian networks allow a directed acyclic graph representation of a causal structure for risk and loss occurrence. Their application presumes that a causal structure for risk propagation can be identified and mapped on to a directed network. The evidence or data available, including subjective information can then be integrated into a formal assessment of risk factors, pathways and potential loss. Different supply chain configurations can be used to assess the change in risk as well as potential expected loss to aid in supply chain risk optimization through an identification of the critical nodes and their risk transference attributes (Archie III & McCormack, 2012; Lockamy III & McCormack, 2010; Mukhopadhyay, Chatterjee, Saha, Mahanti, & Sadhukhan, 2006; Pai, Kallepalli, Caudill, & Zhou, 2003).

## 6.8. Potential Research Questions and Indices for Supply Chain Resiliency

This section of the paper will discuss potential research questions and a hypothesis that were withdrawn in the wake of Thailand's floods, and other cases of supply chain risks.

### 6.8.1. Critical Node and Link

The first research question can be withdrawn because of the fact that the loss is greater if a factory that produces a unique component or plays a critical role in a supply chain is directly impacted by a disaster. This is obvious from the case of Honda or Western Digital in Thailand. When examining the time needed to recover, the electronics sector took longer to recover to "pre-flood" levels of production than the automobile industry for the simple reason that the electronics sector's facilities were more directly damaged by floods.

*Q1: How can critical nodes and/ or links such as assembly factories or transportation hubs whose flooding would lead to significant and persistent supply chain losses be reliably identified in the supply chain network?*

This is also hypothesized from the results of the questionnaire done by METI (2011). Of 55 companies surveyed in Thailand, some 55% pointed out that they had to cease production because their facilities were submerged (Figure 6-11). This number is relatively high compared to the 22% of firms that indicated they had to decrease production due to stagnant procurement from customers adversely affected by the floods. This is consistent with the claim of Fujimoto (2011) that extreme dependence on one supplier can be a "weak link" in a supply chain. Other cases, such as the fire at Aisin Seiki (Reitman, 1997)[15] and the damage to Micro Control Unit's (MCU) facilities following the Japanese Earthquake (Renesas Electronics, 2011)[16], also lend qualitative support to this question. Yet, there are a few studies that quantitatively examine this question from the network analysis perspective. Thus, a future study must examine this question.

[15] Aisin Seiki Co., which produced 99% of Toyota's critical valves, had a fire on February 1st, 1997. Because of the Just-in-time system, Toyota kept only enough inventory of the valve for 4 hours of production. Initially Toyota estimated 2 weeks to resume partial production and 3 months for full production. Toyota had to stop all of 20 assembly plants in Japan, and lost 14,000 cars a day. Toyota sent more than 400 engineers to help Aisin to resume operations. In the end, they could recover production in 5 days.

[16] Renesas Electronics Corporation had to stop Naka factory, which is their main factory in Ibaraki that produces MCU for major automakers such as Toyota and General Motors, after the Japanese Tohoku Earthquake and Tsunami in March 2011. Right after the earthquake, they estimated that they could resume partial production in July 2011. Yet, more than 2000 engineers from their business partners helped them to recover, and consequently Renesas could restore operations on April 23rd 2011.

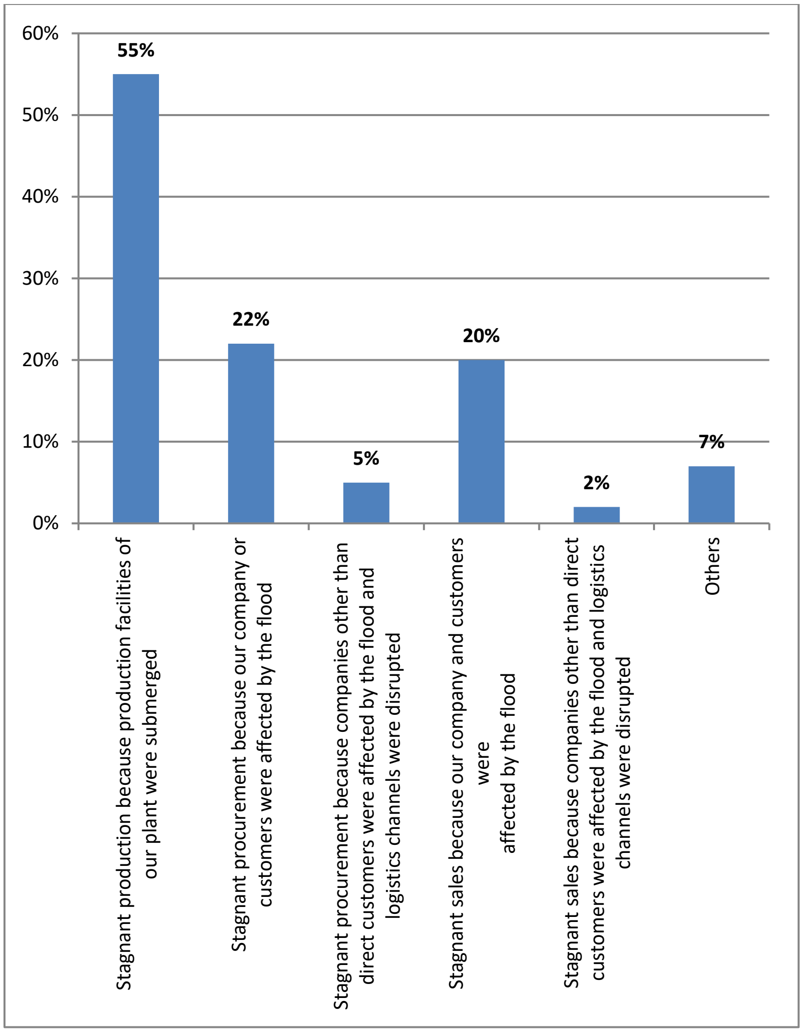



Figure 6-11: Factor or lower production level in Thailand. Total number of manufacturing companies that responded is 55. Multiple choices. *Source*: METI (2011)

### 6.8.2. Alternative Bridge Tie

The second question to be addressed is as follows:

> *Q2: How can the effectiveness of bridge ties to a different supply network be established as an aid to recovery from a flood induced supply chain problem? What are the associated global material supply chain constraints and resulting impacts?*

In the case of the 2011 Thailand floods, Nissan recovered more rapidly than Toyota and Honda because it had diversified its suppliers and owned alternative sources. Yet, given that the alternate bridge will contribute to the resiliency of a supply network, what factors contribute to the establishment of an alternative bridge tie? In order to have an alternative bridge, companies should have design information substitutability (Fujimoto, 2011). By doing so, a company can bring its design to other facilities in a crisis, and manufactures can shift production of their parts to another supplier, or, suppliers can shift their operations to facilities that have not been adversely affected. In the case of the automakers in Thailand, this did not happen, with the result that the auto makers could not transfer their operations, or manufactures could not find other suppliers in the automobile sector. In contrast, the electronics sector was able to transfer production to other countries in response to the lack of production in Thailand (METI, 2012). For example, Toshiba Storage Device relied on an alternate production in Philippines before they restored the Thai factory on February 2$^{nd}$ 2012 after 144 days of shutdown.

The survey conducted by METI (2011) may give some tentative basis to answer this question. For example, some 60% of companies in Thailand could not substitute procurement sourcing because fundamental product design were submerged. However, design substitutability might conflict with the competitiveness of companies that gain an advantage in the marketplace because of their irreplaceable designs (METI, 2011). Therefore, in order to make indices of substitutability, we must consider the balance between substitutability and competitiveness.

### 6.8.3. Strong Ties

Another observed case favoring a well-managed supply chain occurred when Toyota's supplier Aisin had a fire on February 1, 1997, which caused Toyota to lose its supply of brake parts, since Aisin provided 99% of Toyota's valves at that time. Fujimoto (2011) claimed that Aisin resumed operations within one week, although it was originally expected to be out of business for three months. The timeframe for resumption of operations was significantly reduced when Toyota dispatched its engineers to repair Aisin's facility. As a result, even though Toyota was initially expected to incur greater losses as a result of the disruption, since it would lose 14,000 a day (Reitman, 1997) , its intervention minimized the damage. If a company depends only on one company for a specific part, it may incur greater damages, as suggested by H1. Yet, as this case shows, if the ties between the two companies are strong as well as pliable, both companies may be able to avoid some damage. Therefore, the hypothesis is as follows:

*H1: If a supply chain is comprised of strong ties to one company exclusively, then immediate damages from a disaster will likely be greater. Yet, even if business partners in the same supply* *chain network are not directly impacted by disaster, the impacted node may receive help from them and may therefore be able to recover more quickly, with the result that damages may be mitigated.*

Here, the strong ties are defined as repeated, affective, relational exchanges (Lazzarini, Chaddad, & Cook, 2001). Strong ties would promote trust, create social norms, and facilitate cooperation as a consequence (Lazzarini et al., 2001). Though H3 hypothesizes that strong ties would reduce risks to disasters, other studies such as Uzzi (1997) and Afuah (2000) claim that strong ties may induce idiosyncratic features and become less valuable for firm performance in the future. Thus, it is important to examine H4 in the context of resiliency, robustness, and competitiveness of supply networks.

### 6.8.4. Direction of Arrows

The Thailand floods revealed that manufacturing is affected not only by the lack of procurement, but also by decreases in sales. According to the METI survey (2011), of 33 production bases located in Japan, some 66% declined production due to "stagnant sales" because the surveyed companies, their customers (tier 1), or companies under them (tier 2) were affected by the flood, or because logistics channels were disrupted (Figure 6-12). This number is higher than the statistic representing stagnant procurement resulting from flood damage to a company and its customers, which is 33%. Since their customers are affected, producers must reduce production even when they have sufficient capacity. In contrast, in other countries, of 17 companies surveyed, 59% selected "stagnant procurement resulting from flood damage to our company and customers" for their first choice (Figure 6-12). This shows that companies must manage supply chains by looking not only at their supply side, but also at the other side, i.e., the demand side. With this in mind, a modeled network needs to distinguish directions of the link/edge. Thus, the third question is as follows:

*Q3: The direction of links in a network affects the robustness and resiliency of a supply network. How does the complexity of a network, including the direction of links affect the robustness and resiliency of a supply chain network to floods.*

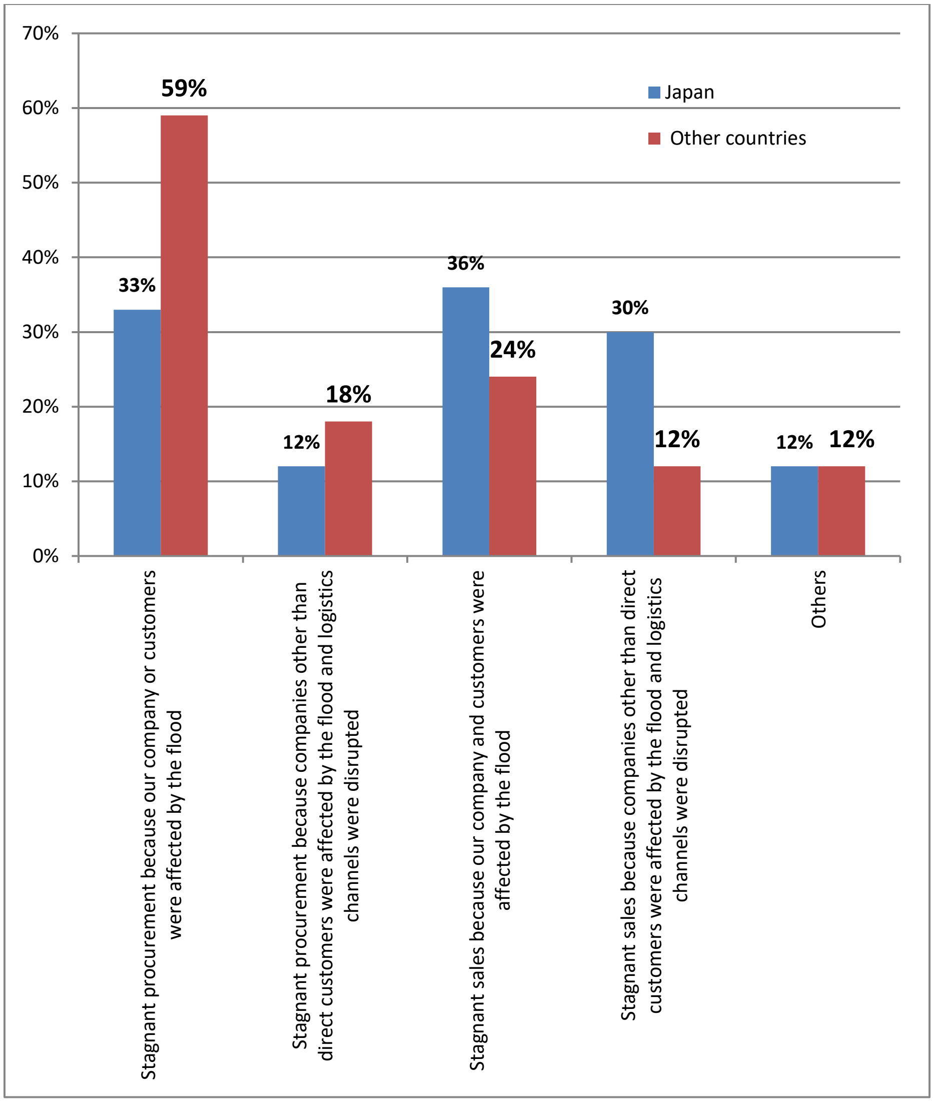



Figure 6-12: Factors of lower production in Japan and other countries. The total numbers of manufacturing companies that responded are 33 for Japan and 17 for other countries. Multiple choices. *Source*: METI (2011)

### 6.8.5. Supporting Policies

These hypotheses are related to the factors that this study proposes as indices, such as *locations of facilities, alternate locations of production, the diversified sources of procurement, emergent assistance from other partner companies in the same supply chain, and degree of the recovery of customers.* The next question is which policies could generate the types of factors found to determine these resilient supply chains. The simulation conducted by Miles and Chang (2003) indicated that the pre-disaster mitigation measures directed at lifeline systems and restoration of transportation system after disasters significantly benefited recovery period for businesses. During the Thai floods of 2011, lifeline and the transportation system had a damage of 57.4 billion Thai Baht (The World Bank, 2012). The damage is relatively lower than the damage in manufacturing sector (1,007 billion Thai Baht) (The World Bank, 2012). Yet, there is a possibility that the loss of the lifeline and transport systems negative would affect the manufacturing sector. There are few studies or reports that examines the interdependencies between lifeline and transport systems and supply chains in the context of resilience to disasters. Thus, the last research question is as follows:

*Q4: How do transportation and lifeline systems affect the performance of entire supply chains during floods?*

## 6.9. Conclusion

The impact of floods in Thailand on the economy in terms of supply chains was examined. Components that should be investigated to assess key supply chain risks from such events were identified. The review suggests that automotive and electronic products supply chains had somewhat different mechanisms of risk transmission and response that translated into different times to recovery, loss and market performance at the individual company level. The need for flood prone countries to consider local risk proofing as part of industrial development was emphasized, both by the nature of the resulting losses to the country and to the global supply chain, and due to the realignment of potential future investment and supplier networks. Regional flood proofing could benefit from systemic risk analysis and its use in infrastructure design, land use zoning, water infrastructure operation, transportation systems functioning, and climate and flood forecasts. Resilience in the supply chains of those who had higher inventories and alternate suppliers was demonstrated consistent with the expectation of supply chain performance under disruption. This brings up the question of how best supply chains could be optimized considering market, production, inventory and disruption due to natural hazards.

Surveys show that most of the affected companies want to operate in the same locations and indeed, they answered that Thailand is still an attractive place for their investment. Given the fact that the Chao Phraya basin has had recurrent floods, unless proper measures are provided, similar disasters may happen again in the near future. The government has announced some measures to prevent future floods, but private sectors must also take proper preventive and responsive measures in their investment decision-making.

Companies have to maintain competitiveness while increasing resiliency. Costs might increase when manufactures ask their suppliers to diversify risk and procurement sources. Thus, it is important to identify how they can build resiliency in a more efficient way without losing their economic competitiveness, which is a critical consideration in future research.

By examining the case study of Thailand and other cases related to extreme events and their concurrent risks, this study suggests four research questions and one hypothesis using the concept of Network Analysis.

> Q1: How can critical nodes and/ or links such as assembly factories or transportation hubs whose flooding would lead to significant and persistent supply chain losses be reliably identified in the supply chain network?
>
> Q2: How can the effectiveness of bridge ties to a different supply network be established as an aid to recovery from a flood induced supply chain problem? What are the associated global material supply chain constraints and resulting impacts?
>
> H1: If a supply chain is comprised of strong ties to one company exclusively, then immediate damages from a disaster will likely be greater. Yet, even if business partners in the same supply chain network are not directly impacted by disaster, the impacted node may receive help from them and may therefore be able to recover more quickly, with the result that damages may be mitigated.
>
> Q3: How does the complexity of a network, including the direction of links affect the robustness and resiliency of a supply chain network to floods?
>
> Q4: How do transportation and lifeline systems affect the performance of entire supply chains during floods?

These hypotheses are related to the factors that this study proposes as indices, such as *locations of facilities, alternate locations of production, the diversified sources of procurement, emergent assistance from other partner companies in the same supply chain,* and *degree of the recovery of customers.*

Future research must conduct quantitative analysis to examine the resiliency and robustness of supply chains to disruptions caused by extreme events, and to formulate a way to reduce vulnerability to risks while maintaining competitive edge. In so doing, a future study can propose the potential effectiveness of different strategies for risk management in such situations, ranging from redundancy in the supply chain, increased inventory to targeted insurance, and their combination. As well, it should develop and use climate and weather forecasts to take defensive action.

# CHAPTER 7. A STRATEGY FOR PARAMETRIC FLOOD INSURANCE USING PROXIES


## Abstract

Traditionally, the design of flood control infrastructure and flood plain zoning require the estimation of return periods calculated by river hydraulic models and rainfall-runoff models. However, this multi-step modeling process leads to significant uncertainty when assessing inundation. Changes in land use and climate alter the potential losses and can make the modeling results obsolete. For these reasons, there is a strong need to create parametric indexes for the financial risk transfer for large flood events to enable rapid response and recovery. This study examines the possibility of developing a parametric flood index at the national or regional level in Asia, which can be quickly mobilized after catastrophic floods. Specifically, we develop a single trigger based on rainfall index as well as a multiple trigger-based index using rainfall and streamflow indices for Bangladesh and Thailand applications. The proposed methodology is 1) select suitable indices of rainfall and streamflow (if available), 2) identify trigger levels for specified return periods for losses using stepwise and logistic regressions, 3) measure the performance of indices, and 4) derive return periods of selected windows and trigger levels. Based on the methodology, trigger levels were identified for Bangladesh and Thailand. Models based on multiple triggers reduced basis risks, an inherent problem for index insurance. Such parametric flood indices can be applied for ex-ante risk financing for developing countries.


## 7.1. Introduction

Economic losses caused by floods exceeded 19 billion USD in 2012 (Munich Re, 2013a; Ward et al, 2013) and have increased over the past 50 years (IPCC 2012; UNISDR 2011; Ward et al 2013). Traditionally, there are two main applications for riverine and urban flood risks that require the estimation of a design return period: (i) the design of flood control infrastructure; and (ii) flood plain zoning in a river and coastal area. In both cases, hydraulic models using either streamflow data or rainfall data with rainfall-runoff models have been used to estimate the flood risk as characterized in a flood frequency curve, from which “peak discharge” associated with different return periods is identified for the specified design return period. The flow depth or inundation area is computed from this peak flow estimate using a hydraulic model. The resulting flood maps are also utilized to estimate potential losses. This type of risk estimation framework is typical for flood insurance programs.

This multi-step modeling process leads to significant uncertainty. The representativeness of rainfall data used is difficult to assess for the actual type of inundation. Further, rainfall-runoff model parameters are typically calibrated to available historical events that may be much smaller than those considered a 100-year flood, and hence the representativeness of the resulting flood hydrograph and inundation comes into question. Finally, the event-based methodology tends to ignore composite events or sequences or space-time clusters of extreme rainfall events. In many cases, extreme floods result from the large scale recurrent transport of moisture into the region of interest (Lu, Lall, Schwartz, & Kwon, 2013; Nakamura, Lall, Kushnir, Robertson, & Seager, 2013), and these do not fit well into the intensity-duration-frequency design paradigm that is typically used with synthetic events. As a result of the combined effect of these factors, the flood plain zoning for a high return period event, e.g., the 100-year flood, is marked by an unknown bias and uncertainty, which translates into a challenge for assessing potential values at risk. Particularly for local assets and rare event exposure, the actual risk is very hard to estimate even after considerable data collection and modeling efforts. In addition, land use change and a changing climate alter the potential losses as well as the nature of the rainfall-runoff river hydraulics relationships over time, making the modeling results obsolete. Updating such models is resource-intensive. This situation is compounded by inter-annual to multi-decadal climate variability and anthropogenic climate change, both of which change the frequency and intensity of rainfall events and land cover, which in turn alter runoff generation and flood risk.

Rapidly assessing damages and losses after disasters is critical so that communities and governments can quickly make progress in recovery and reconstruction. So far, the assessments have been conducted mainly at the ground level. Since a methodology requires existing social, economic and physical data that developing nations often lack, it is often a challenge for developing nations to assess damages and losses quickly after disasters. For a catastrophic event, governments may not be able to mobilize funds, depending on the size of a reserve fund, for disaster response. Loss verification is usually time-consuming, and insurance payments can consequently be slow.

In the practice of disaster risk finance, ex-ante and ex-post financing are the two main types of risk financing for disaster risk management. Ex-post financing, such as budget reallocation, domestic and external credit, tax increases, and donor assistance, can take a long time to negotiate (i.e., emergency loans) and can be highly variable and unpredictable (i.e., donor's assistance) (The World Bank, 2012). Thus, relying on these ex-post financing instruments alone would increase the financial instability and uncertainty for national governments. This does not mean that ex-post financing is not necessary for reconstruction after disasters, but it has some limitations in terms of efficiency (The World Bank, 2012a). In contrast, utilizing ex-post risk financing, including parametric insurance, will decrease this financial uncertainty while increasing efficiency. Governments usually need a great deal of financial resources for the reconstruction only several months after a disaster. Before the reconstruction starts, governments require fewer financial resources for relief operations and responses to liquidity shortage immediately after a disaster (The World Bank, 2012).

For these reasons, there is a need to create parametric indexes for the financial risk transfer for large flood events in order to enable rapid response, recovery and reconstruction. These flood indices could be established based on rainfall indices that use long term records and rainfall sensors to reduce uncertainty, modeling time, and verification and calibration associated with hydrologic models. The parametric insurance product based on a rainfall index would be designed to be triggered independent of actual loss verification so that stakeholders can mobilize resources rapidly. A challenge in designing a rainfall index is to cover antecedent data that captures the actual spatio-temporal risks, including the duration, extent and severity of inundation. Namely, the index should minimize basis risk and account for the representative exposure pathways for an application. A basis risk refers to the imperfect correlations between payouts determined by the index and actual losses caused by the hazard (Barnett & Mahul, 2007). It is possible that policyholders will receive index insurance indemnity without actual losses, and vice versa. If the index can be priced based on estimated occurrence likelihood with low basis risk, an effective coverage consistent with anticipated needs for individuals and governments can be designed. Changing risks affected by climate change can be priced as forecasts become available.

A few parametric ex-ante risk financing schemes exist for the earthquake and tropical cyclone at the country or regional scales. For example, the government of Mexico issued the catastrophe bond CatMex2006 under parametric trigger coverage in 2006 to transfer seismic risks to the international market. In addition, 16 governments in the Caribbean created the Caribbean Catastrophe Risk Insurance Facility for earthquake and hurricane risks in 2007 (The World Bank, 2012a). Though index insurance for floods targeting individual farmers exists in some countries (i.e., in Vietnam and Peru), no parametric flood index targeting national governments exists. Compared to other hazards, floods can have significant spatial heterogeneity in impacts and damage compared to other types of hazards, such as earthquakes or droughts. This is a challenge when using index insurance for floods.

### *Literature review for existing flood indices.*

Several flood indices are developed using precipitation data. Müller et al. (2015) developed the flood extremity index (FEI). FEI, along with other indices of weather and precipitation extremes, can reflect not only maxima of precipitation amounts and peak discharges at individual gauges but also the rarity of values, the size of the affected area, and the duration of precipitation (Müller et al., 2015). However, it is not clearly understood how to use the index as a threshold to trigger payout for insurance.

Another index is the Standardized Precipitation Index (SPI) (Mckee, Doesken, & Kleist, 1993). This index was initially designed to monitor the status of drought in Colorado, but it has also been used to monitor the wet conditions. To calculate the SPI, a gamma distribution is fit to the distribution of the observed data (McKee et al, 2993) in a time series of at least 30 years without any missing data (Wu, Hayes, Weiss, & Hu, 2001). Other studies propose a flood index to measure the severity of flooding using hydrographs from past flood characteristics (Ahn & Choi, 2013; Bhaskar, French, & Kyiamah, 2000).

The criteria to assess extreme climate events are discussed (Cioffi, Lall, Rus, & Krishnamurthy, 2015; Du, Wu, Li, et al., 2013; Du, Wu, Zong, Meng, & Wang, 2013):

1) The absolute, arbitrary or fixed threshold method. A climate event in excess of a specific value is considered as an extreme.

2) The standard deviation method. An event that exceeds k-standard deviation is defined as an extreme.

3) The percentile-based method. An event that exceeds a specified percentile of the empirical marginal distribution is considered as an extreme. This method is popular because it can be applied to a region with a heterogeneous climate (Cioffi et al., 2015).

This study uses the percentile-based method using a standardized anomaly, $z$, which is defined as follows:

$$\mathrm{z} = \frac{x - \mu}{\sigma}$$

, where μ is a mean while $\sigma$ is a standard deviation.

No systematic statistical evaluation of how precipitation index's behavior relates to a local proxy of flood hazards, such as flooded areas, has been made in the context of index insurance and risk transfer. If such an index could function for risk transfer, it would have some advantages over ground-based flood indices because it can be rapidly mobilized. An advantage is that it cannot be manipulated by policyholders because it indexes the physical mechanisms that influence flooding and does not require direct loss estimates that could be inflated or be difficult to assess.

This paper is similar to the methodology of Khalil et al. (2007), which proposes ENSO related climate indices as a proxy to extreme rainfall for a flood insurance in Peru. Their study showed that it is feasible to design an index insurance tied to ENSO indices for risk management with some lead time (up to 6 months). In contrast, our study is based on rainfall and streamflow indices.

This study explores two approaches to select trigger levels for parametric flood insurance: multiple triggers and a single trigger. If high-quality river discharge is available, the approach of multiple trigger levels is adopted. In contrast, if river discharge data has not been collected extensively in developing nations or the collected data is low quality, a single trigger approach is adopted. The single trigger level approach is used for the Thailand case study while the multiple trigger levels is used for the Bangladesh case study.

### *Objectives of the paper*

The objective of this paper is to explore the potential introduction of rainfall-based flood indices, which can measure a trigger level for payout of index insurance for catastrophic floods in Southeast and South Asia. This study considers country-scale flood indices and index insurance products, rather than a product aimed at individual farmers. The index focuses primarily on solutions for the ministries of finance of developing countries as the target user. The target offerors of the insurance are reinsurers and multilateral financial institutions such as the World Bank. The primary goal of the index insurance is to effectively meet the financial needs of quick response for these target users and offerors to increase the resiliency of public institutions and the economy for the benefit of local residents and evacuees following a catastrophic flood.

The specific questions of interest are:

(1) What is an appropriate space-time average rainfall and streamflow index for flood loss? What is the statistical relationship between flood hazards (such as flood extent, damage, and duration) and rainfall or streamflow indices? How can we estimate the return period associated with levels of this index?

(2) How can we design the flood index for payout based on a trigger level? What is basis risk due to uncertainty associated with the use of the index? What is the applicability of the index designed for Thailand and Bangladesh to other nations in South and Southeast Asia?

These questions are explored using the statistical methodologies and proposed methodology in Section 7.2, which can be extended to other countries with similar geographical and meteorological characteristics.

## 7.2. Proposed Methodology for Parametric Flood Index

A combination of different data sources is proposed to develop a scalable rapid prototyping strategy for a rain induced regional flood risk index that can be readily customized to a particular setting. The general approach proposed below can be extended to other locations than the countries studied in this paper. The intention is to provide an index that is suitable for a macro level regional project for index risk from an extreme event. As a second step, local organizations may disaggregate the risk index to potential local exposure mapping, and secondary insurance or financial products at the local level that are effectively backed up or reinsured by the regional index. As these disaggregated products are deployed by a local agent, the need for the magnitude of the index purchase or re-insurance would become directly evident. Thus, a scalable strategy that links traditional insurance and structural flood risk instruments to a regional index, or directly uses a regional index for coverage, becomes available.

*Data*

The primary data sources can include:

1) Historical inundation data from a variety of remote sensing sources – Landsat, Sentinel, etc. available through NASA and other satellite sources, government data, and the Colorado Flood Observatory. Area and duration of inundation, as well as estimates of damages or people affected may be available. For our case study, data from a national government and the Colorado Flood Observatory (DFO) are used. DFO[17] data have been available since 1985. The information in the dataset is derived from news media, governmental, instrumental and remote sensing sources and records data such as the number of affected people, economic damages, and affected flood areas. As recognized by data collectors, repeated flooding is a complex phenomenon and they strive for a compromise between aggregating and separating flood events.

2) Daily and sub-daily rainfall records at different resolutions are available from a variety of global climate data products based on observations, climate re-analysis, sub-seasonal to seasonal climate forecasts, and climate scenarios for future conditions. The re-analysis data sets may include up to a century of data, which provides the opportunity to reduce the uncertainty associated with short inundation records. The primary problem with rainfall records in developing countries is missing data or low-quality data. For example, in Bangladesh, only nine stations among all 34 meteorological stations has long-term (more than 50 years) daily rainfall data with less missing data than in more spatially diverse parts of the country (Shahid, 2011). This study uses two kinds of precipitation data: gauge-based and reanalysis data, which are available globally for more than 100

[17] http://www.dartmouth.edu/~floods/Archives/

years. This allows a better characterization of risk in time variation than the typical short term local records in developing countries, which are often used with rainfall-runoff models.

3) Daily streamflow and water level data from major contributing river systems are used if available. For our study, streamflow and water level data is used for Bangladesh.

### 7.2.1 Overall Strategy for the Proposed Methodology

The overall strategy is summarized in Figure 7-1. The first step is to select suitable rainfall windows by conducting correlation analysis using the top 20 events. The second step is to identify trigger levels for specified return periods for losses by calculating z-scores of rainfall windows that were selected in the first step. Stepwise regressions or correlation analysis are used to select significant predictors. Then, a logistic regression is used to determine the trigger level that are evaluated based on performance measures called sensitivity and specificity. The final step is to identify return periods of rainfall windows and trigger levels selected in step 1 and step 2. The return periods are calculated using a threshold approach in the extreme value theory (Coles, 2001).

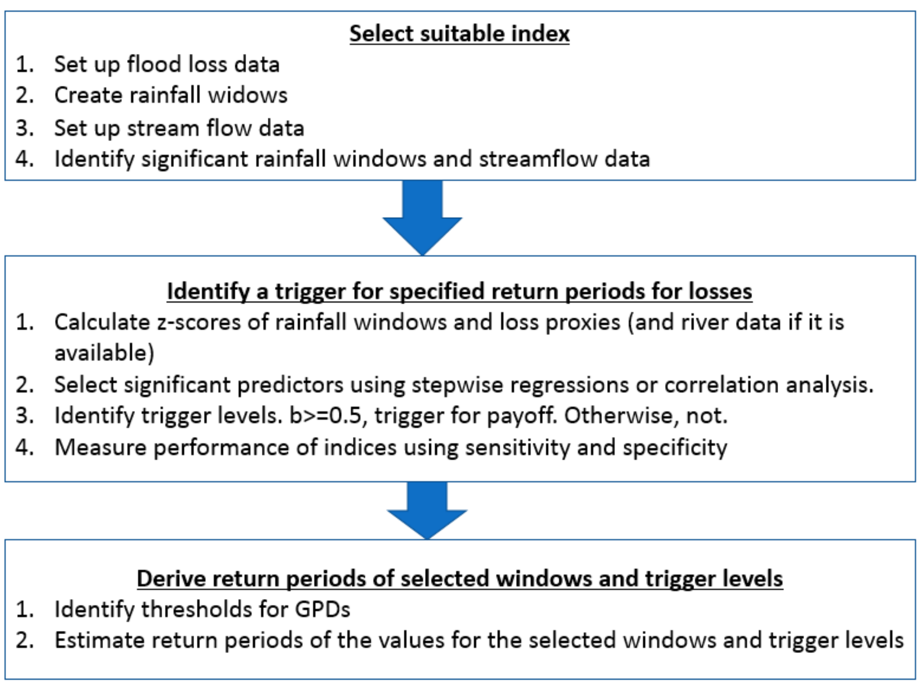



Figure 7-1: Research procedure of this study

### 7.2.2 Specific algorithms in each step

A detailed algorithm for each step is as follows:

**Step1: Select Suitable Index**

a. **Set up flood loss data.** Satellite based inundation data is available for approximately 30 years for most of the earth. For the regional flood index for the region of interest, let us consider that a data set of maximum area inundated per event $A_i$, i=1…I is available, over the n years of record, such that we retain only those events for which the inundated area is greater than some nominal threshold $A^*$. The corresponding date $t_i$ and duration $d_i$ of each event can also be extracted from the data using procedures similar to those used by the Colorado Flood Observatory, or taken directly from their pre-processed data. For each event i, from the hydrologic drainage network we can identify the contributing drainage area for the inundated section of the region. Let us label this as $C_i$.

b. **Create rainfall windows.** From the rainfall data set identify $P_{i,\tau}, \tau = 1 \ldots. T$, which is an index for selected durations of rainfall, e.g., 1 day, 3 days, 5 days , …30 days, and $P_{i,\tau,t}$ is the precipitation averaged over $C_i$ over a duration $\tau$ preceding the date of inundation $t_i$. We are interested in identifying a duration of rainfall that is best correlated to the potential inundation. For large area inundation, the extreme rainfall over the contributing area over 1 day immediately preceding the flooding is likely to be important. However, prior rainfall amounts in the immediately preceding days or even the prior week may also be important, since they would have contributed to runoff as well as the saturation of soil moisture leading to enhanced runoff for the most recent day. Consequently, we may be interested in an index that covers one or more time scales for precipitation, and would like to identify this from the data.

c. **Setup streamflow data if it is available.** From the streamflow and water level data, identify total or maximum streamflow, $SF_{ir}$ and water level $WL_{ir}$ for each river system r. In the case of Bangladesh, there are three main river systems to consider: the Brahmaputra, Ganges, and Meghna Rivers.

d. **Identify significant rainfall windows and streamflow data, if it is available, for significant predictors.** Typically, the $P_{i,\tau}$ will be highly correlated for different values of $\tau$ , and hence a classical stepwise regression approach, using methods such as lasso or local regression, or correlation analysis based on rank, to choose the best values of  to predict $A_i$ or $d_i$ from an appropriate subset of the $P_{i,\tau}$ may not be robust. From a pragmatic perspective we would like to design an index such that no more than 2 values of $\tau$ are considered for our final index. These would correspond to the immediate rainfall and rainfall over an appropriate pre-conditioning period. Then for the region of interest, we consider a selection problem for $\tau'$, to maximize the conditional log likelihood:

$$LL = \sum_{i=1}^{n} \log(f(A_i | P_{i1,} P_{i\tau'}, )) \tag{1}$$

The conditional probability model would be fitted to an appropriate linear or nonlinear model relating $A_i$ to $P_{i1}$ and $P_{i\tau'}$ , using an appropriate multivariate model, e.g., a generalized Pareto distribution for $A_i$. Let's term this Model $M_1$.

When $SF_{ir}$ and $WL_{ir}$ are available, consider a selection problem for predictors for $SF_{ir}$ and $WL_{ir}$, maximize the conditional log likelihood:

$$LL = \sum_{i=1}^{n} \log(f(A_i | P_{i1,} P_{i\tau'}, SF_{i,r'}, WL_{i,r'}, )). \tag{2}$$

**Step2: Identify trigger levels for specified return periods for losses**

1. **Calculate z-scores of rainfall windows and loss proxies (and river data if it is available).** A standardized anomaly, z, as defined before, needs to be calculated as a preliminary.

2. **Select significant predictors using stepwise regressions or correlation analysis.** Let's consider only the extreme inundation events, which have a return period greater than R years. A binary time series $b_i$, $i=1…I$ such that $b_i$ = 1 if $A_i > A_R$, and 0 otherwise. $A_R$ can be estimated by any method appropriate for a partial duration series (since there may be multiple events per year). Next we consider a generalized linear model with a logisitic link function between $b_i$ and $P_{i1}$ , $P_{i\tau'}$ , $SF_{ir}$, and $WL_{ir}$. Then

one can use BIC, AIC or Lasso to select the appropriate $\tau'$ and the predictors. Note that only $P_{i1}$ may be selected by either procedure suggested.

3. **Identify trigger levels.** Let us say that the selected logistic model is

$$b = \beta_0 + \beta_1 P_{i1} + \beta_2 P_{i\tau'} + \beta_3 SF_{i,r} + \beta_4 WL_{i,r} \quad (3)$$

Then if a selected combination of ($P_{i1}, P_{i\tau'}, SF_{i,r}, WL_{i,r}$) leads to b=0.5, then this combination corresponds to a median prediction of $A_R$. This implies that our index can be defined as b, and a value of b≥0.5 constitutes an exceedance of $A_R$ and reflects a payout condition.

This approach is similar to the ones proposed by Khalil et al (2007). If a flood hazard series, such as flood affected areas, is directly used to specify a trigger threshold for index insurance then the trigger level is the value of the series corresponding to a desired probability of exceedance, $Prob_{exc}$. For example, $Prob_{exc}$=0.25 corresponds to an event with a return period of 4 years. The corresponding threshold can be identified from an observed cumulative distribution function of a historic series of flood affected areas under the assumption that the flood affected areas are independently and identically distributed.

(1) Let's say that $Prob_{exc}$ is 0.25. A corresponding threshold $A^*$ such that the flood area is exceeded on average with probability $Prob_{exc}$ can be identified. This is the 75th percentile of the flood area as given

$$\mathrm{E}\,[\,\mathrm{prob}(\mathrm{A} > A^*)] = 0.25 \quad (4)$$

(2) We can identify a trigger value $P_{i\tau}, SF_{ir}, or\ WL_{ir}$ for different predictors, such that on average the probability of exceedance of the corresponding threshold for the flood area is the desired probability $Prob_{exc}$. Given that we use several significant predictors, we expect that if a certain threshold $A^*$ is exceeded then on average a corresponding threshold $P_{i\tau}^*, SF_{ir}^*, WL_{ir}^*$ is exceeded with some probability. We aim to identify such an $A^*$.

(3) For flood affected areas *A*, consider the binomial process as $b_i$ as before ($b_i$=1 if $A>A^*$, $b_i$=0 if $A<A^*$). Considering a logistic regression of $b_i$ on $P_{i\tau}, SF_{ir}, WF_{ir}$, we can estimate the conditional probability $\mathrm{E}[\mathrm{prob}(b_i |\, P^*_{i\tau}, SF^*_{ir}, WL^*_{ir})]$

4. **Measure the performance of indices using sensitivity and specificity.** To measure performance of predictors (or classifiers) using a trigger level, a contingency table is created (Figure 7-2). Each case is recorded with either positive (p) or negative class (n) labels. Namely, the positive class means a case when a flood event is recorded above a certain degree; the negative one means a case when a flood event is not recorded below the same threshold. A classifier is a prediction of a flood or not. To make a distinction between the actual class and the predicted class, we use the labels {Y, N} for the class predictions by a model. There are four possible outcomes following a predicting classifier and actual instance (Figure 7-2). We will use a true positive rate (sensitivity) and a true negative ratio (specificity).

| | Actual status: Floods | Actual status: No Floods |
|---|---|---|
| Predicted status: Floods | True Positive | False Positives |
| Predicted status: No floods | False Negatives | True Negatives |

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negatives}$$

$$Specificity = \frac{True\ Negative}{False\ Positive + True\ Negatives}$$

Figure 7-2: Contingency table and its performance metrics after Fawceet (2006).

The above approach is based on flood event *i*. However, we can make the same approach for annual data. For the annual data, for a year *t*, we define $P_{t,season,r}$, $SF_{t,season,r}$, and $WL_{t,season,r}$. Based on the above approaches, we present our case studies using data from Thailand and Bangladesh.

**Step 3: Estimate Return Periods**

Return periods of both selected windows and trigger levels can be estimated. To estimate return periods in this study, Generalized Pareto Distribution (GPD) in the extreme value theory is used. GPD has a theoretical justification for fitting to a threshold excess approach (Coles, 2001; Gilleland & Katz, 2016), as given by

$$H(x) = 1 - \left[1 + \varepsilon\left(\frac{x-\mu}{\sigma_\mu}\right)\right]_{+}^{-1/\varepsilon}$$

where μ is a high threshold, x> μ, scale parameter $\sigma_\mu$>0 and shape parameter $-\infty < \varepsilon < \infty$. The shape parameter $\varepsilon$ determines three types of distribution functions: heavy-tailed Pareto when $\varepsilon$>0, upper bounded Beta when $\varepsilon$<0. The exponential is obtained by taking the limit as $\varepsilon \to 0$, which gives

$$H(x) = 1 - e^{-(x-\mu)/\sigma}$$

Return periods are calculated in the following way:

(1) Select a common 30-year period for flood attributes and rainfall. For example, if the rain statistic selected is the 30day rainfall (*W30c)* for the entire country centered around the flood event then W30cm, the smallest W30c value of flood-associated rainfall that led to a flood damage is identified.

(2) Using 100-year rainfall data, identify all *W30* events that could cause a flood loss. First, identify all rainfall amounts using a 30-day moving window. Second, retain all events for which W30c > W30cm. Third, choose the top 10$^{th}$ percentile of the W30c values as a threshold.

(3) Finally, use the Generalized Pareto Distribution (GPD) to estimate the return period of any potential trigger event for a catastrophic loss.

## 7.3. Parametric Index with a Single Trigger – Case Study of Thailand

A single trigger level based on rainfall is presented using the case of Thailand. The area of the Chao Phraya River basin is 160 thousand km$^2$ and consists of approximately 30% of the total land of Thailand (Komori et al., 2012). The large flood events occurred in 1831, 1942, 1983, 1995, 1996, 2002, 2006, and 2011 (Aon Benfield, 2012). The flooding in 1995 was ranked the highest in terms of flooded area (444 thousand km$^2$) (Gale & Saunders, 2013) while the flooding in 2011 was the highest in terms of economic damage (46.5 billion USD) (The World Bank, 2012b).

### 7.3.1. Data

***Flood area data***

Flood data, such as beginning and end dates, flooded areas, flood durations, and damages associated with floods, are obtained from DFO. For Thailand, since 1985, there are 68 recorded flood events. Among them, 34 events record economic losses. The median flooded area is 50,000 km$^2$. The median flood duration is 11.5 days, while the maximum flood duration is 158 days. The dataset includes large flood events in 1995, 1996, 2003, and 2004 (Figure 7-3).

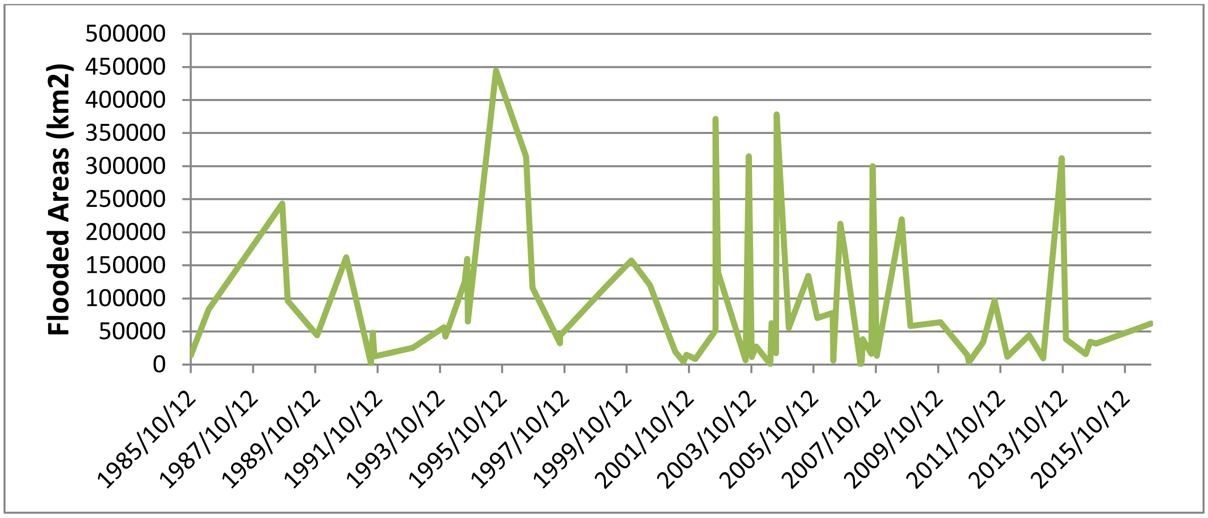



Figure 7-3: Time series of flooded areas in Thailand.

### *Precipitation data*

The observational precipitation data is an average of CPC 0.5 over the whole country from January 1st of 1979 to January 9th of 2017, while the reanalysis data is ERA-20C/ ERA-interim (ECMWF) from 1900 to the present (Table 7-1). Three different windows are created and are based on: a day when a flood began, a day when a flood ended, and the middle of a flood period.

Table 7-1: Description of precipitation products used in the study

| Precipitation Data | Description |
|---|---|
| CPC 0.5 | The U.S. National Oceanographic and Atmospheric Administration's Climate Prediction Center (NOAA/CPC) provides a gauge-based analysis of daily precipitation constructed over the global land areas. Gauge reports are collected from more than 30,00 stations. Daily analysis is constructed on a 0.125 degree resolution, and released on a 0.5 degree grid from 1979 to the present (Xie 2010). |
| ERA-20C/ ERA-Interim | ERA-20C is an atmospheric data from 1900 - 2010. The spatial resolution is approximately 125km. ERA-interim is global atmospheric reanalysis data from 1979 that is continuously updated in real time. The spatial resolution of the dataset is approximately 80 km. Both are mean daily precipitation. |

Table 7-2: Correlation coefficients (Kendall's τ) between rainfall windows, flooded areas and durations using observational and reanalysis data.

| | 1-day window | 2-day window | 3-day window | 4-day window | 5-day window | 10-day window | 30-day window |
|---|---|---|---|---|---|---|---|
| CPC 0.5 | | | | | | | |
| Areas | 0.16 | 0.17 | 0.18 | 0.16 | 0.18 | 0.20 | 0.20 |
| Duration | 0.11 | 0.10 | 0.12 | 0.12 | 0.15 | 0.25 | 0.28 |
| ERA/ERA-interim | | | | | | | |
| Areas | 0.15 | 0.14 | 0.15 | 0.17 | 0.17 | 0.23 | 0.22 |
| Duration | 0.13 | 0.08 | 0.10 | 0.12 | 0.14 | 0.23 | 0.23 |

### 7.3.2. Analysis

#### *7.3.2.1. Correlation with Precipitation Amounts*

The rainfall index is selected in the following ways both for observational and reanalysis data:

1. Identify the events for which we have data on flood area, duration, and loss.
2. Estimate the rainfall over the country or basins for windows of {1,2,3,5,10,30 days} around the date of the event for each such event.
3. Identify which window for rainfall gives the best correlation with the flood statistics using the Mann-Kendall method.
4. Explore the relation of flood loss to area, duration and selected rain statistics to ensure that this is a good choice.
5. Repeat the analysis both for the dataset using all the data and the one using only the top 20 events, which are selected in terms of area, duration and damage.

The correlation between flood hazards and rainfall amounts with different rainfall windows was first examined using both the full flood data and the top 20 events in terms of flooded area, duration, and damage. Flood data since 1985 were obtained from the Dartmouth Flood Observatory (the DFO). The results showed that the 30-day window offers the most accurate correlations ($\tau = 0.36$) compared to other rainfall windows, while the 5-day window is the second most accurate ($\tau = 0.31$). Other results are shown in Table C-1 in Appendix C.1: Correlation Analysis Results for Thailand.

#### *7.3.2.2. Designing the flood index for Thailand*

A rainfall-based index was able to be created because the association between rainfall and flood extent was reasonably well established, since no major river originates from outside the country. The correlation analysis selected 5- and 30-day windows for □. Here we only use the reanalysis data (ERA/ERA-interim) that have higher correlations than the CPC's data. Stepwise regression based on AIC suggests that a model with a 10-day window achieves the lowest AIC value (AIC=56.6). Therefore, these 3 windows are selected as the best windows to identify an insurance payoff trigger level. For the purposes of demonstration, a selected $Prob_{exc}$ is 0.2, which is the 80$^{th}$ percentile of the flood area's index (Figure 7-4,Figure 7-5,and Figure 7-6).

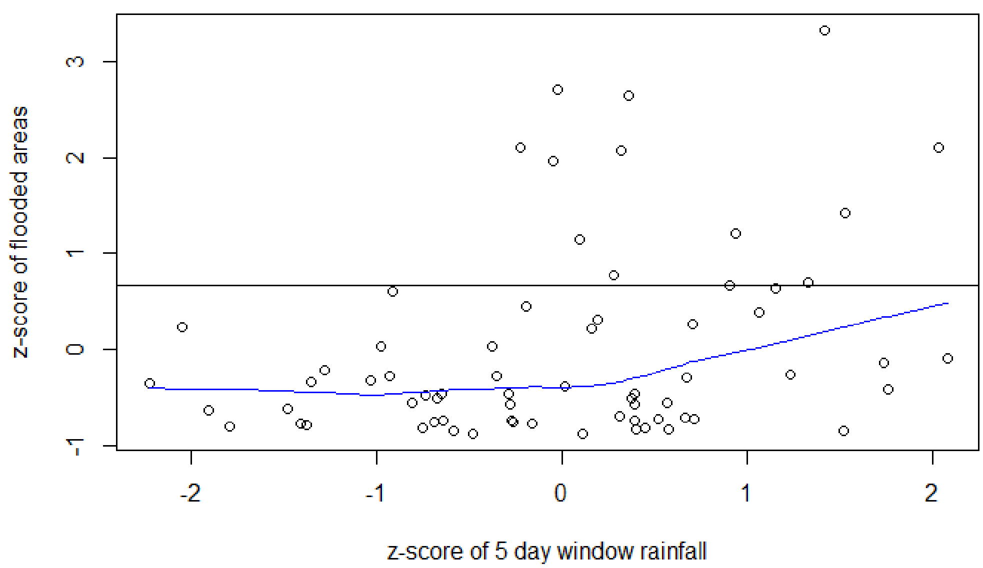



Figure 7-4: Flood areas versus the 5 day window rainfall using 68 events since 1985. The horizontal line represents the 80$^{th}$ percentiles of the distribution of the flood areas based on 68 events of data, and the blue curve represents a lowess smooth of the data.

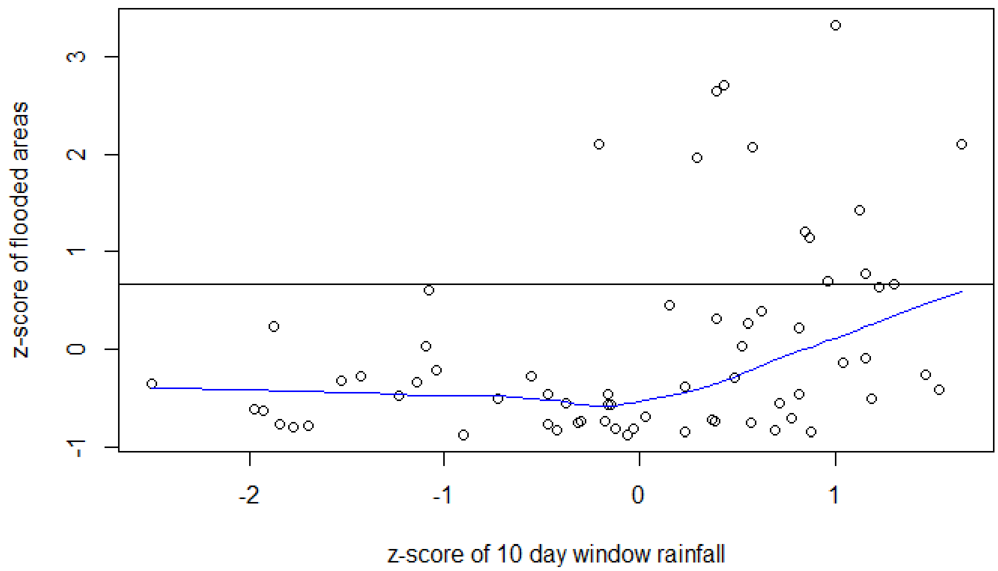



Figure 7-5: Flood areas versus the 10 day window rainfall using 68 events since 1985. The horizontal line represents the 80th percentiles of the distribution of the flood areas based on 68 events of data, and the blue curve represents a lowess smooth of the data.

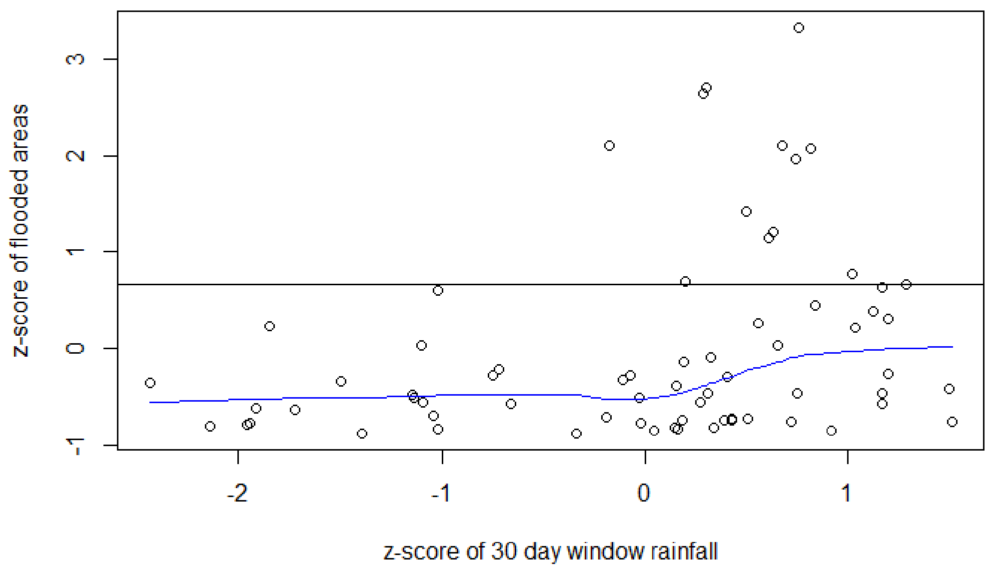



Figure 7-6: Flood areas versus the 30-day window rainfall using 68 events since 1985. The horizontal line represents the 80$^{th}$ percentiles of the distribution of the flood areas based on 68 events of data, and the blue curve represents a lowess smooth of the data.

We consider the binomial process, $b_i$ as $b_i$=1 if $A>A^*$, $b_i$=0 if $A<A^*$, where $A^*$ is the 80$^{th}$ percentile of the flood area. Then, we first estimate the following single logistic regressions:

$$b = \beta_0 + \beta_1 P_{i5} \quad (5)$$

$$b = \beta_0 + \beta_1 P_{i10} \quad (6)$$

$$b = \beta_0 + \beta_1 P_{i30} \quad (7)$$

Among three models, Model 6, which uses the 10-day window, achieves the lowest AIC value (Table 7-3).

Table 7-3: Result of single logistic regressions of b on the 5-day, 10 day, or 30 day windows for the 80the percentile floods.

| Coefficients | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| *Model 5* (AIC=62.16) | | | | |
| $\beta_0$ | -1.71 | 0.38 | -4.5 | 6.69e-06 *** |
| $\beta_1$ | 1.00 | 0.38 | 2.59 | 0.00955 ** |
| *Model 6* (AIC=56.6) | | | | |
| $\beta_0$ | -2.11 | 0.52 | -4.08 | 4.59e-05 *** |
| $\beta_1$ | 1.68 | 0.59 | 2.86 | 0.00431 ** |
| *Model 7* (AIC=63.54) | | | | |
| $\beta_0$ | -1.73 | 0.40 | -4.32 | 1.52e-05 *** |
| $\beta_1$ | 1.04 | 0.48 | 2.20 | 0.0282 * |

For multivariate logistic regressions, we selected the models based on AIC. The lowest AIC is Model (8) as below (Table 7-4).

$$b = \beta_0 + \beta_1 P_{i3} + \beta_2 P_{i4} + \beta_3 P_{i10} \quad (8)$$

Table 7-4: Result of the multivariate logistic regression of b on the 3-day, 4-day, and 10-day windows of Model (8).

| Coefficients | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Model 8 (AIC=54.3) | | | | |
| $\beta_0$ | -2.28 | 0.56 | -4.05 | 5.03e-05 *** |
| $\beta_1$ | -4.21 | 1.99 | -2.11 | 0.0342 * |
| $\beta_2$ | 4.15 | 2.23 | 1.86 | 0.0625 . |
| $\beta_3$ | 1.62 | 0.82 | 1.97 | 0.0488 * |

Using these estimated coefficients, the probability, *Prob*, that the flood area series will exceed the specified threshold, conditional on precipitation window values, $P_{i10}$ and $P_{i3,i4,\ i10}$ is estimated as

$$\text{prob} = \frac{1}{1+\exp(-z_i)} \quad (9)$$

For $P_{i10}$, we have the following estimated equations:

$$z_i = -2.11 + 1.69P_{i10} \tag{10}$$

$$z_i = -2.28 + -4.21P_{i3} + 4.15\,P_{i4} + 1.62P_{i10} \tag{11}$$

Consequently, for the 80th percentile, the estimated trigger level $P_{10}$ of Model (6) is 1.25 as a z-score for the 10 day window rainfall (Figure 7-7). For Model (8), $P_{i10} + 2.60P_{i3} - 2.56P_{i4} \geqq 1.41$ is a trigger level (Figure 7-8). In Figure 7-8, the trigger level is above the colored plain. In conclusion, for the case of Thailand, if either of these two models exceeds these thresholds they reflect payout conditions.

Sensitivity and specificity are calculated to measure the performance of the triggers (Table 7-5). Specificity values (0.96 and 0.92) are relatively high, while the sensitivity values (0.15 and 0.23) are not . The basis risk associated with this trigger level not being triggered during an actual occurrence of flood is still high given the low value of sensitivity (0.15 and 0.23). Therefore, further studies are needed to improve the index while attempting to increase sensitivity. Future studies might consider using streamflow data for Thailand, given that the situation improved in Bangladesh with water level data included (discussed in section X).

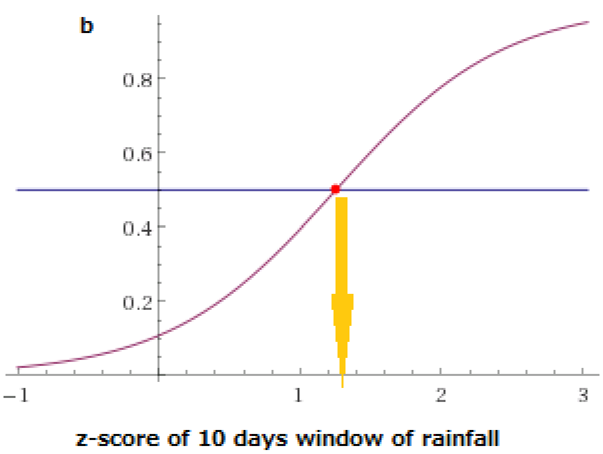



Figure 7-7: Predicted E [Prob|Pi10] from the logistic regression. The trigger level is greater than 1.25361 of the z-score of the 10 day window rainfall for the 80th percentile flood.

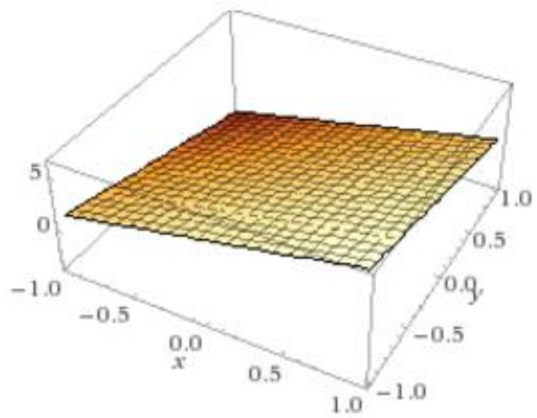



Figure 7-8: Predicted E [Prob|Pi3, Pi4, Pi10] from the logistic regression. The trigger level is Pi10 + 2.59677Pi3-2.56061Pi4 ≧1.40767 for the 80th percentile floods. The trigger level is above of the colored plain.

Table 7-5: Contingency table for model (6) and model (8)

| | 80th percentile flood occurred ($b_i$=1) | 80th percentile flood did not occurred ($b_i$ = 0) |
|---|---|---|
| Model (6) | | |
| b ≧0.5 (pay out) | 2 | 2 |
| b < 0.5 (no payout) | 11 | 53 |
| | Sensitivity =2/13=0.15 | Specificity = 53/55=0.96 |
| Model (8) | | |
| b ≧0.5 (pay out) | 3 | 4 |
| b < 0.5 (no payout) | 10 | 51 |
| | Sensitivity =3/13=0.23 | Specificity = 51/55=0.92 |

#### *7.3.2.3. Return periods of Selected Rainfall Windows and Trigger Levels*

Return periods of the selected rainfall windows and trigger levels are calculated in order to derive the exceedance probabilities of these criteria. First, the 5- and 30-day windows are selected because they have the highest correlations. The selected threshold is at the 90th percentile. It is 77 mm for the 5-day window while it is 347 mm for the 30-day window (Table 7-6).

The differences in precipitation amounts in each return level seem relatively small. For example, the corresponding rainfall amounts are 84mm/ 5days for a 2-year level while 94 mm/5days for a 100-year level. This is because we took average precipitation amounts for the entire country. It is possible that rainfall amounts of each return level would vary much more widely based on specific regions. Namely, geographical basis risk was higher in the case of a single trigger in Thailand.

Return levels of the trigger level using $P_{i10}$, which is 1.25 as a z-score, is 16.7 years (94th percentile) for Model (6).

Table 7-6: Return levels and corresponding rainfall amounts for the selected rainfall windows based on the correlation analysis.

| | 5-year level | 20-year level | 100-year level |
|---|---|---|---|
| 5-day window (mm/ 5 days) | 88 | 91 | 94 |
| 10-day window (mm/10 days) | 162 | 168 | 172 |
| 30-day window (mm/30 days) | 402 | 414 | 425 |

## 7.4. Parametric Index with Multiple Triggers – The Case Study of Bangladesh

Bangladesh is located in the delta of three of largest rivers in the world, the Ganges, Brahmaputra, and Meghna Rivers and has suffered from flooding due to its vulnerable geographical character. Approximately 92.5% of the river basins of these three rivers are located outside of Bangladesh (Mirza, 2003). The extreme floods in 1987, 1988, and 1998 inundated approximately 70% of the country and caused huge mortality and economic damages, especially in rural areas (Mirza, 2003). Recent floods in 1988, 1998, 2004, and 2007 caused losses from one to two million metric tons of rice, which is equivalent to 4 – 10% of the annual rice production (A. S. Islam, Haque, & Bala, 2010). Floods in 2004 alone caused economic losses of approximately 1.6 billion USD (K. M. N. Islam, 2005).

Several studies since then have analyzed mechanisms and measures for catastrophic floods. Mirza (2003) examines the external and internal precipitation regimes and hydrological aspects associated with the catastrophic floods in 1987, 1988 and 1998. Yang et al. (2014) investigate flood damage functions specific to Bangladesh. Some efforts have been made to design flood index for the application to index insurance in Bangladesh. Bhattacharya et al. (2016) proposes a flood index based on hydrograph characteristics such as the rising curve gradient, flood magnitude ratio, and time to peak for the northeastern region in Bangladesh. Some attempts have started at the community level to create flood indices in Bangladesh. The International Water Management Institute along with others conducted a pilot project for community-level flood index insurance in Sirajganj, Bangladesh (Desai, 2013). Yet, to our knowledge, no comparable work exploring flood indices for the application to index insurance at the country scale in Bangladesh exists.

The same methodology as the analysis for Thailand is used to examine the correlation between flood hazards and different windows of rainfall in Bangladesh. However, due to the complex nature of floods in Bangladesh, streamflow data (discharge and water level) in their primary river systems (the Brahmaputra, Ganges, and Meghna Rivers) were added to the analysis.

### 7.4.1. Data

#### *Flood areas data*

Since DFO data has some problems in data quality, this study refers to Bangladesh Water Development Board (BWBD, 2014), which produces an annual report on flooding situations in Bangladesh since in 1954. This annual basis data recorded the catastrophic floods in 1955, 1974, and 2004 (Mirza, 2003). Since BWBD is government official data and referred by other studies such as Yang et al. (2014) and Ozaki (2016), BWBD data for the purpose of demonstrating a methodology is used as a primary alternative to the DFO data. Please refer to Appendix C.2: Bangladesh's Flood .

#### *Precipitation data*

We use two types of precipitation data: gauged-based analysis data and reanalysis data. The gauged precipitation data is CPC 0.5 average over the whole country since January 1st of 1979 to January 9th of 2017. Reanalysis data is from 1900 to the present (ERA/ ERA-interim, ECMWF). First, three different windows were created and were based on: a day when a flood began, a day when a flood ended, the middle of a flood period. This study uses the data when a flood began because they showed the highest correlation in our preliminary analysis. The monsoon season between June and September is critical since over 80% of annual precipitation falls in the season (Mirza, 2003).

#### *Streamflow data*

We use streamflow data, which are available for three main river systems that flow into Bangladesh: Bahadurabad for The Brahmaputra River, Rajshashi for the Ganges River, and Bazar Meghna for The Meghna River (Table 7-7). Each location is shown in Figure 7-9. Though the preliminary work analyzed both streamflow discharge data and water levels of these rivers and other rivers, this study uses only water level data of the main three rivers because of gaps in the streamflow data. For the detailed analysis of streamflow and water levels in river systems in Bangladesh, please refer to Appendix 4.

The long-term average annual total runoff into Bangladesh is 355, 642, and 149 billion cubic meters from the Brahmaputra (Mirza, 2003), Ganges (Yang et al., 2014), and Meghna River (Yang et al., 2014) respectively. Water levels in the Brahmaputra and Menha start to rise between mid-April and early-May and peak between July and August while that of the Ganges River begins to rise between mid-May and early-June and peaks in August or September (Yang et al., 2014). We assume that the relationship between water level and discharge volume is not significantly nonlinear for water level data as also assumed by (Yang et al., 2014). Therefore, there is space for improvement in a future study, since these sediment heavy rivers may not have a good approximation as claimed by (Hopson & Webster, 2010).

Seasons for rainfall and streamflow data are categorized into 3 seasons: summer (March – May), rainy (June-Sept), and winter (Oct – Feb). Streamflow and water level data are collected and analyzed from three stations from main three river systems: Bahadurabad in Brahmaputra River (abbreviated *bahad*), Rajshashi in Ganges River (abbreviated *rajsh*), and Bhairab and Bazar in Meghna River (abbreviated *bhair*). For example, water levels in Bahadurabad during rainy season for a year of *t* is shown as $WL_{t,rainy,bahad}$.

Table 7-7: List of streamflow and water level data

| Site | Type |
|---|---|
| **Water level** | |
| Daily water level at Bahadurabad (m)[2] | Daily water level (April 1949 – Oct 2009) missing values are 4%. |
| Daily water level at Rajshashi (m)[2] | Daily water level (April 1922 – Dec 2006) Ethan, missing values are 25% (mostly April 1938 – Dec 1957). |
| Daily water level at Bhairab Bazar (m)[2] | Daily water level (April 1959 – July 2006), missing values are 17%, |

Source: Yang et al.(2014)

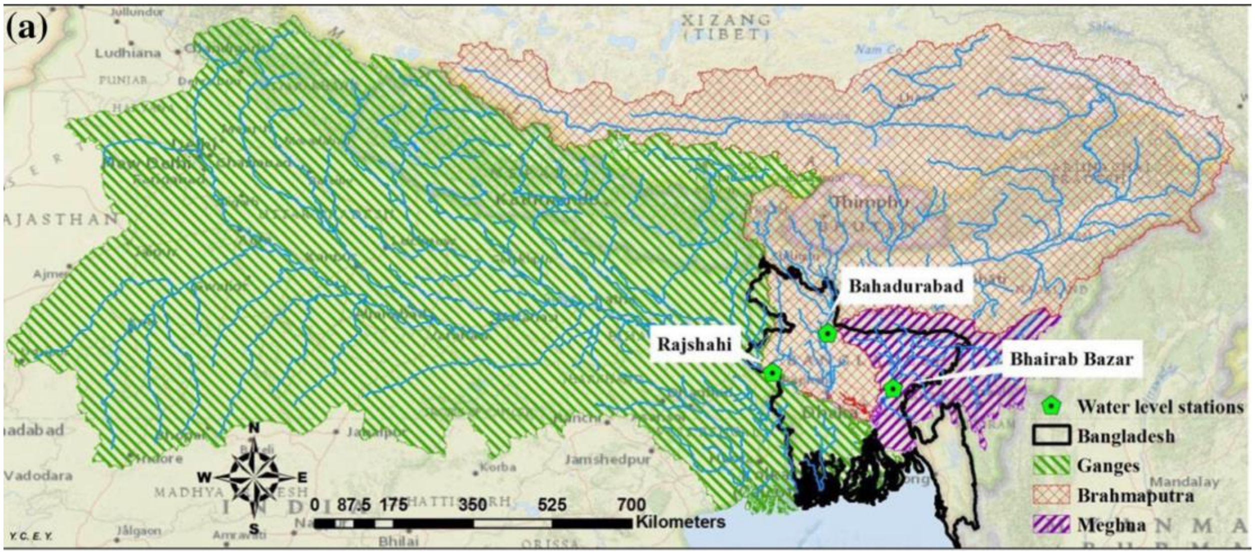



Figure 7-9: Locations of streamflow and water level data used. Adapted from Yang et al (2015)

### 7.4.2. Analysis

#### *7.4.2.1. Preliminary Analysis with Precipitation Amounts, Streamflow and Water Level*

Flood event dates were not available because the BDWB data is an annual basis, , which makes ore analysis more challenging. For precipitation data, the annual maximum rainfall amounts for each window are calculated to estimate correlations with the annual flooded affected areas using the same procedure as the one used for Thailand (Table 7-8 and Figure 7-10). Rainfall data used here is Reanalysis ERA and ERA interim data. Although shorter rainfall windows, such as the 1-day and 2-day windows, showed the highest correlation coefficients (0.11) among other windows, they were not as strongly correlated with catastrophic flood events.[18] The patterns of the standardized anomaly based on the rank, especially the top 10 events, are also examined. For this analysis, the seasonality in the data was first removed. These results indicate that no single significant predictor can be used as a threshold for floods. However, precipitation in the rainy season has positive standardized anomalies with flooded areas, especially with the highest flooded events.[19] Therefore, it is necessary to use combinations of predictors based on logistic regressions.

[18] Please see the details in Appendix C.3: Analysis of Rainfall, Streamflow, and Water Level Data in Bangladesh
[19] Detailed results are shown in Appendix C.5: Analysis of Standardized Anomaly in the Streamflow and Water Levels in Bangladesh

Table 7-8: Correlation Coefficients between flooded areas and different rainfall windows (Kendall τ)

| | 1-day w | 2-day w | 3-day w | 4-day w | 5-day w | 10-day w | 30-day w |
|---|---|---|---|---|---|---|---|
| Annual Flood affected Areas | 0.107 | 0.115 | 0.057 | 0.050 | 0.042 | 0.053 | 0.039 |

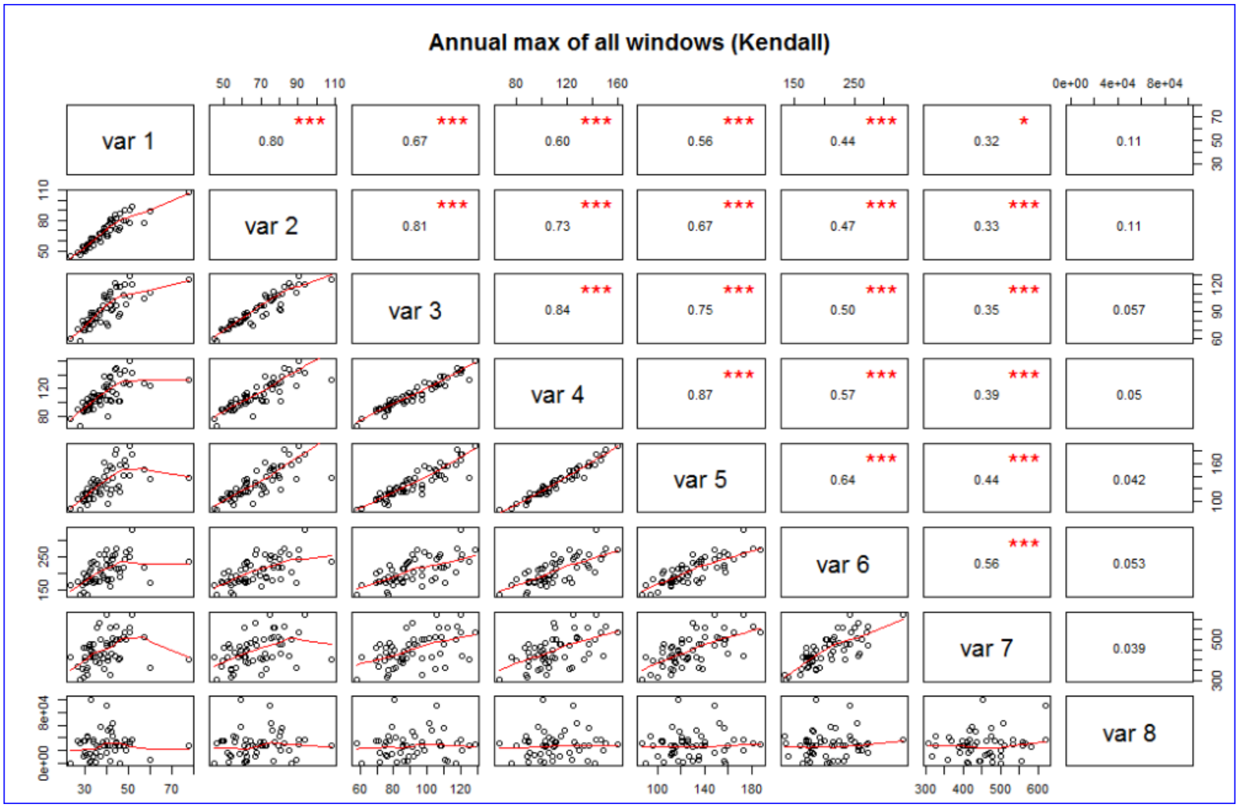



Figure 7-10: Correlation Coefficients between flooded areas and different rainfall windows (Kendall τ). Var1 is the 1-day window, Var2 is the 2-day window, Var3 is the 3-day window, Var4 is the 4-day window, Var5 is the 5-day window, Var6 is the 10-day window, Var7 is the 30-day window, and Var8 is flood affected areas.

### 7.4.2.2. Designing flood index for Bangladesh

The multi trigger levels for flood index are examined because the rainfall index alone does not show high correlations due to the influence from streamflow in the three main rivers originating outside of the Bangladeshi territory. Based on the standardized anomaly analysis above, rainy season precipitation is selected as one of the predictors. Stepwise regression suggests that below Model (12) – (14), using water level data during rainy seasons in Bahadurabad (Brahmaputra River) and Bhairab and Bazar (Meghna River), achieves the lowest AIC value. These three models are selected to identify an insurance payoff trigger level. For the demonstration purpose, a selected $Prob_{exc}$ is 0.1, the 90th percentile of the flood areas index in Figure 7-11-Figure 12.

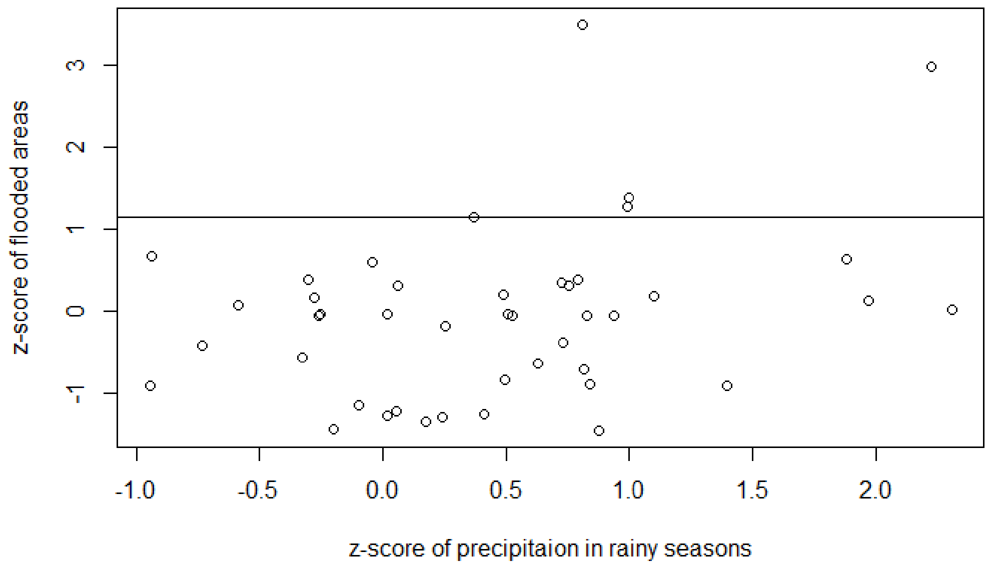



Figure 7-11: Flood areas versus precipitation during the rainy season using 46 years events between 1960-2005. The horizontal line represents the 90th percentiles of the distribution of the flood areas based on 46 years of data.

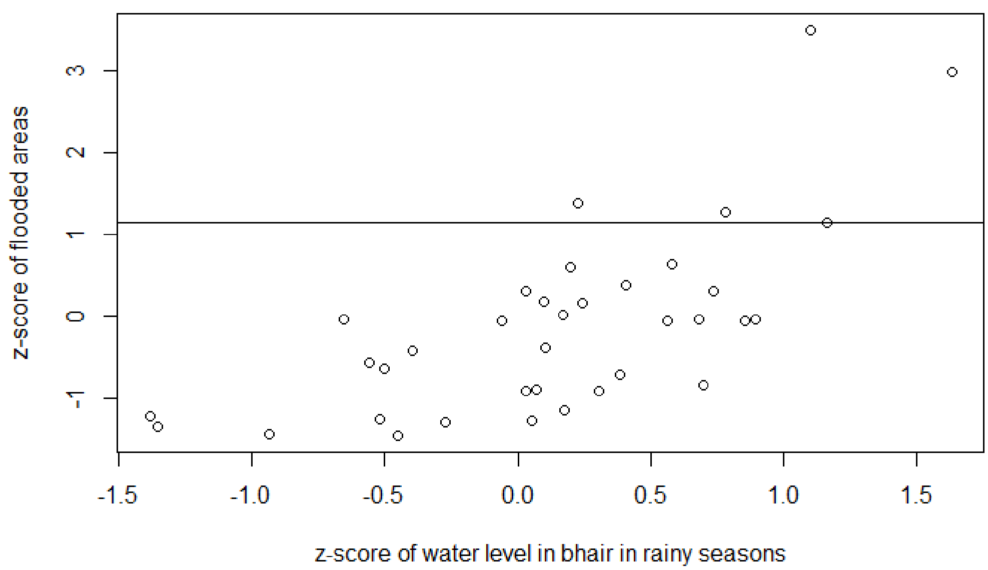



Figure 7-12: Flood areas versus water level in bhair during the rainy season using 46 years events between 1960-2005. The horizontal line represents the 90th percentiles of the distribution of the flood areas based on 46 years of data.

We consider the binomial process, $b_i$ as $b_i$=1 if $A>A^*$, $b_i$=0 if $A<A^*$, where $A^*$ is the 90th percentile of the flood area Figure 7-11. Then, we estimated the following logistic regressions:

$$b = \beta_0 + \beta_1 P_{t,rainy} \tag{12}$$

For multivariate logistic regressions, we selected the models based on AIC. The lowest AIC is Model 13 and 14 as below.

$$b = \alpha_0 + \alpha_1 P_{t,rainy} + \alpha_2 WL_{t,rainy,bhair} \tag{13}$$

$$b = \alpha_0 + \alpha_1 WL_{t,rainy,bahad} + \alpha_2 WL_{t,rainy,bhair} \tag{14}$$

Table 7-9: Result of the logistic regressions. Model 12 is the logistic regression of b on water level in rainy season in Bhairab and Bazar; Model 13 is the logistic regression of b on rainyP and water level in rainy season in Bhairab and Bazar; Model 14 is the logistic regression of b on water level in rainy season in Bahadurabad and rainy season in Bhairab and Bazar.

| Coefficients | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| Model 12 | | | | |
| $\beta_0$ | -4.350 | 1.590 | -2.735 | 0.00623 ** |
| $\beta_1$ | 4.571 | 1.993 | 2.293 | 0.02184 * |
| Model 13 | | | | |
| $\beta_0$ | -5.339 | 2.281 | -2.341 | 0.0192 * |
| $\beta_1$ | 1.054 | 1.169 | 0.902 | 0.3671 |
| $\beta_2$ | 4.874 | 2.295 | 2.124 | 0.0337 * |
| Model 14 | | | | |
| $\beta_0$ | -4.110 | 1.696 | -2.423 | 0.0154 * |
| $\beta_1$ | -2.952 | 5.396 | -0.547 | 0.5844 |
| $\beta_2$ | 5.456 | 2.771 | 1.969 | 0.0490 * |

Consequently, for 90th percentile of the flooded area, the esimated trigger level $P_{i,}$ rainy is 0.95 as a z-score for rainy season's preciptation (Table 7-10). For Model 14 - 16, the trigger levels are expressed in a linear function. For Model 13,

$$P_{rainy} + 0.216249 * WL_{t,rainy,bhair} \geq 1.0954$$

, while for Model 14,

$$WL_{t,rainy,bahad} - 0.541056 * WL_{t,rainy,bhair} \geq 0.753299 .$$

For these, the trigger levels are above the linear lines. Payout conditions are reflected if either of these models exceed these thresholds.

Table 7-10: Trigger levels for Model 12 - 14

| Models | Linear predictor of $z_i$ | AIC | Trigger levels |
|---|---|---|---|
| Model 12 | $z_i = -4.350 + 4.571\, WL_{t,rainy,bhair}$ | 19.96 | 0.95 |
| Model 13 | $z_i = -5.339 + 1.054\, P_{t,rainy} + 4.874\, WL_{t,rainy,bhair}$ | 21.10 | $P_{t,rainy} + 0.216249 * WL_{t,rainy,bhair} \geq 1.0954$ |
| Model 14 | $z_i = -4.110 + -2.952\, WL_{t,rainy,bahad} + 5.456 WL_{t,rainy,bhair}$ | 21.69 | $WL_{t,rainy,bahad} - 0.541056 * WL_{t,rainy,bhair} \geq 0.753299$ |

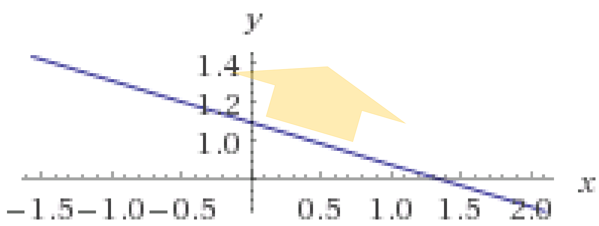



Figure 7-13: A trigger line of Model 13. The x axis is a z-score of water level in Bhairab and Bazar in rainy seasons while the y axis is a z-score of rainfall in rainy seasons. The upper right part above the line is the trigger level area.

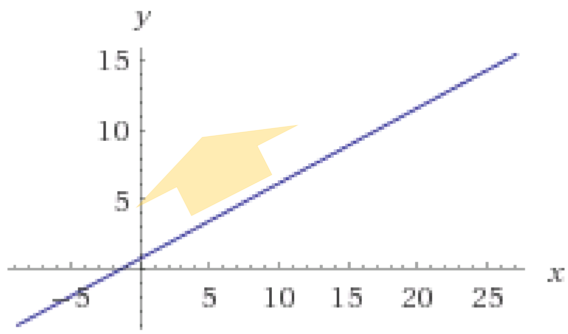



Figure 7-14: A trigger line of Model 14. The x axis is a z-score of water level in Bhairab and Bazar in rainy seasons while the y axis is a z-score of water level in Bahadurabad in rainy seasons. The upper left part above the line is the trigger level area.

To examine a true positive and true negative ratio, sensitivity and specificity are calculated when using these trigger levels (Table 7-11). Specificity values (1.0, 0.87 and 1.0) are relatively working better than those in Thailand. The sensitivity values (0.6, 0.4, and 0.6) are also better than those found in Thailand. Thus, the addition of water level predictors in a multiple trigger model leads to the improvement of model performance.

Table 7-11: Contingency table for Model 12 – 14 in Bangladesh.

| | 90th percentile flood occurred ($b_i$=1) | 90th percentile flood did not occurred ($b_i$ = 0) |
|---|---|---|
| *Model 12* | | |
| b >=0.5 (pay out) | 3 | 0 |
| b < 0.5 (no payout) | 2 | 33 |
| | Sensitivity =3/5 = 0.6 | Specificity = 33/33=1.0 |
| *Model 13* | | |
| b >=0.5 (pay out) | 2 | 4 |
| b < 0.5 (no payout) | 3 | 27 |
| | Sensitivity =2/5=0.4 | Specificity =27/31=0.87 |
| *Model 14* | | |
| b >=0.5 (pay out) | 3 | 0 |
| b < 0.5 (no payout) | 2 | 31 |
| | Sensitivity =3/5=0.6 | Specificity =31/31=1.0 |

#### *7.4.2.3. Return Levels of Selected Rainfall Windows and Trigger Levels*

Return levels of the selected rainfall windows and trigger levels are estimated based on a threshold approach using GPD (Coles, 2001). Using this time windows selected in 7.4.2.1 and threshold of the 90th percentile, the return periods of the selected rainfall windows are first estimated in Table 7-12. The trigger levels derived in 7.4.2.2 are also estimated. The trigger level of 0.95 as a z-score in Model 12 has the return levels of 12.5 years (92th percentile).

Table 7-12: Estimated return periods and corresponding rainfall amounts for the selected rainfall windows based on the correlation analysis.

| | 2-year level | 20-year level | 100-year level |
|---|---|---|---|
| 1-day window (mm/1 day) | 97.5 | 145.7 | 194.9 |
| 2-day window (mm/2 days) | 150 | 199.6 | 301.5 |

## 7.5. Discussions

This study examines the possibility of developing a parametric flood index at the national or regional level in Asia, both with a single and multiple trigger levels. Several detailed investigations into the exceedance probability for flood event impacts were pursued in order to calculate the return periods of floods in Bangladesh and Thailand. This work is intended to be a preliminary work supporting future work on pricing risk transfer mechanisms in ex-ante risk finance.

### *Applicability of the approach to other countries*

The approach of the single trigger level used for Thailand in this study can be applied to countries having similar characteristics to Thailand. Thailand's topography is flat and rainfall is brought by monsoons and tropical storms. The two main rivers (Chao Phraya River, and Mun and Chi Rivers, which are tributaries of the Mekong River) originate in Thailand. Countries with similar topography with major rivers and river basins originating in their territories can use the approach of a single trigger level with globally available gridded rainfall products. Malaysia is possible candidate in Southeast Asia that can adopt a single trigger index .

In contrast, the multiple trigger approach can be applied to countries with similar topographical and meteorological characteristics to Bangladesh. Bangladesh's topography is flat with elevation. Even though precipitation in Bangladesh is brought by monsoons and tropical storms, the three main rivers (Brahmaputra, Ganges, and Meghna Rivers) originate outside the country. Only 7.5% of the catchment areas of the three main rivers lie in Bangladesh and 92.5% lie outside the country. These reasons required us to use streamflow data in addition to precipitation analysis to analyze Bangladesh. This approach can be applied to other countries in Southeast Asia, such as Cambodia, Laos, Myanmar and Vietnam because their major rivers, such as the Mekong River, originate in neighboring countries.

### *Utility of the Approach*

This study demonstrated that a parametric index for flood insurance can enable risk management to be more efficient and robust. First, the parametric index proposed by this study does not need tremendous time and resources typically required to build a conventional runoff model. The index can be created using publicly available gridded-precipitation and streamflow data. Offering parametric insurance in monsoon Asia would enable the countries in the region and donors, such as the multilateral development institutions, to quickly respond to catastrophic floods. Second, this study suggests that the parametric index can be extended to create a larger risk pool in Asia. Due to the law of large numbers, if we can pool a large number of uncorrelated or negatively correlated risks, we can make risk management more robust by lowering the variance of payouts and increasing the total size of the pool (Khalil et al., 2007). To accomplish this, future studies should examine spatial and temporal dependence of extreme precipitations in South and Southeast Asia in the context of a parametric flood index.

### *Possible Issues of the Approach*

In addition to benefits, there are also concerns in implementing a parametric flood index. First, the case study of Thailand shows that accurate long-term hazard data, such as extreme precipitation and streamflow data, are important, yet not always available. Another issue is that heterogeneous regions with many micro-climates have higher basis risk. To address these limitations, more accurate data should be collected from diverse locations and future studies should address the heterogeneity of rainfall.

The Bangladesh case study demonstrates that the biggest obstacle in implementing this proposed parametric index is the availability of long-term, accurate hazard, exposure and vulnerability data. In this case there are still large discrepancies in estimates of flooded areas among different sources. The direct use of flood estimates might be an option, but flood extent is not currently well estimated . Historic DFO and BWBD data and the result of processed remote sensing products are not consistent with each other (Figure 7-11). The Bangladesh study highlights the need for data to be publicly available and centralized (The World Bank, 2012a). To create an effective parametric index, transparent and accurate risk information is required (The World Bank, 2012a).

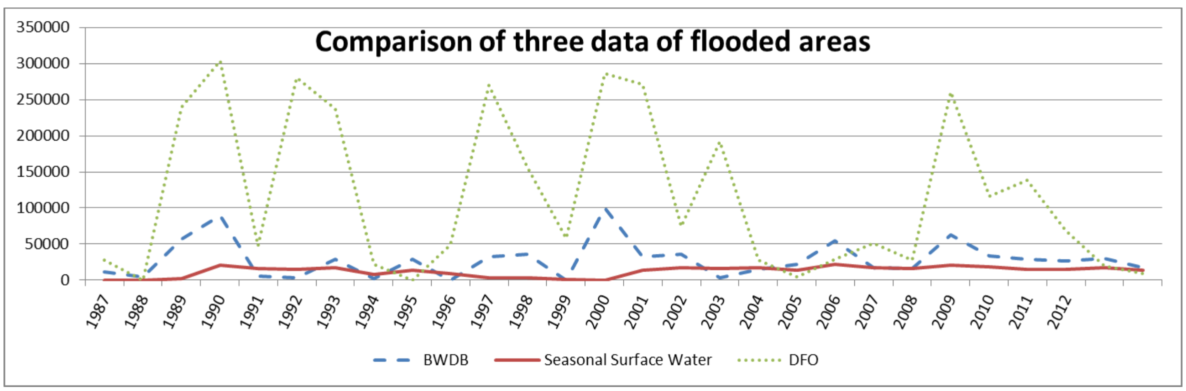



Figure 7-15: Comparison of the three data sets for flood affected areas in Bangladesh.

Though this study did not specifically explore this issue, another possible challenge to macro-index insurance is the national or regional government's concern that the purchase of such a product would disincentivize donors to provide ad hoc financial support during catastrophes (Miranda & Farrin, 2012). To address this concern, partnership with donor agencies or multilateral financial institutions are desirable (Miranda & Farrin, 2012)

### *Addressing Basis Risk*

Basis risk is an inherit problem in a parametric insurance (Chantarat, Mude, Barrett, & Carter, 2013). Firstly, basis risk is a tradeoff between several other problems. For example, the characteristics that cause basis risk also eliminate asymmetric information problems (Barnett, Barrett, & Skees, 2008). Trade-off also exists between transaction costs and basis risk (Barnett et al., 2008; Nell & Richter, 2000). Collecting accurate rainfall and streamflow data from diverse stations improves basis risk but also incurs additional transaction costs. Furthermore, tradeoff exists between moral hazards and basis risk (Croson & Kunreuther, 2000; Doherty, 1997; Doherty & Richter, 2002). If the index is triggered by physical indices, such as hurricane's intensity and location, these parameters cannot be controlled by the insurer, meaning there is no moral hazard.

Minimizing basis risk is critical for the success of a parametric index (Barnett & Mahul, 2007; Khalil et al., 2007; Miranda & Farrin, 2012; The World Bank, 2012a). If a part of basis risk, false negative probability - a probability that the insured will not be indemnified even when losses occur- is large, the value of the index insurance for the insured would be low (Elabed, Bellemare, Carter, & Guirkinger, 2013). This study shows how to improve the basis risks associated with the parametric index for flood insurance, especially in terms of false negative probability.

To reduce basis risk, the performance of flood index in Bangladesh with multiple triggers was better in terms of sensitivity and specificity than the case of a single trigger in Bangladesh and Thailand. This is partly because water level data contributes to improving the index performance. This is consistent with the results by Elabed et al. (2013), which analyzes a multiscale index insurance contract that reduces basis risk relative to conventional, single-scale index insurance contract. Future studies should address basis risk, especially for sensitivity perspective.

To minimize basis risk, improving the collection of hazards, exposure and vulnerability data at the ground level, including damage and loss data, is critical. In addition, improving monitoring systems is essential for generating accurate hazard data (The World Bank, 2012a). For example, a promising solution is remote sensing. Chantarat et al. (2013) shows that satellite-based vegetation data in near real time with the combination of finer livestock data can minimize basis risk in Kenya. In future work, a perfect simultaneous acquisition of optical and SAR data over a flooded area would be desirable to improve the estimates of flooded areas (Lall, Ceccato, Allaire, Cian, & Haraguchi, 2017). Higher resolution data below the district level will be useful, too.

## 7.6. Conclusions

### *Contribution of this study*

The proposed design for parametric flood insurance could improve the design of parametric-based approaches to risk transfer in developing nations and increase their resiliency to natural disasters, ultimately advancing sustainable and resilient development. The increased understanding of flood index will enhance the market expansion of parametric-related financial products, including index insurance, catastrophic bonds, index-based derivatives, and insurance-linked securities. The parametric-based financial products have some advantages in terms of independence and objectivity. For example, the products that adopt indices produced by independent third-parties are free of manipulation or moral hazards by the insured. In addition, promoting the use of ex-ante insurance can reduce the contingent liability of governments and help increase the resilience of society as a whole (The World Bank, 2012a). To our knowledge, no comparable study examining the statistical attributes of flood indices at the national level exists. The work presented here can be used as a template for the investigation of creating parametric risk transfer in other countries.

### *Issues and countermeasures*

This case study showed that basis risk still exists, and it is critical to collect long-term accurate data on flood hazards, exposure and vulnerability. There are several areas that researchers can pursue in future studies.

First, the approach in this study can be improved by harnessing recent technological development in remote sensing techniques. Satellite-based emergency mapping is most intensively deployed in Asia and Europe, proportionally following the geographic, physical, and temporal distributions of natural disasters (Voigt et al 2016). Remote sensing technologies could expedite the damage and loss assessment, enabling governments to quickly accelerate the recovery and reconstruction phases, such as dispersing insurance payments quickly. At the present, one of the current challenges is cloud penetration (Lall et al., 2017). Lall et al. (2017) process satellite images from Sentinel-1 and LANDSAT to estimate flood extent, depth, and duration. Flood depth is approximated with a Digital Elevation Model (DEM). For example, flood detection in July-August 2015 in Bangladesh is not possible due to cloud cover (Lall et al., 2017). The detection of flood during July and August can only be performed using SAR data (Lall et al., 2017). However, Sentinel 1 and LANDSAT show a high agreement after removing variables such as clouds and permanent water. After these processes, the statistics to assess uncertainties are the following: 0.72 for the Kappa Coefficient, 0.78 for Probability of Detection (PDO), and 0.69 for Critical Success Index (CSI) (Lall et al., 2017). If a more accurate estimate of flooded areas for the precedent floods could be obtained, models that investigate relationships between rainfall and flooded areas would improve and eventually contribute to the improved understanding of the design of flood indices.

Second, the index products can be improved by combining other types of indices or financial schemes. For example, the use of exposure data, such as a modelled loss index, will improve basis risk of the parametric index (The World Bank, 2012a). Other ex-ante risk transfer products are also useful to complement parametric flood insurance. For example, creating a common insurance pool for flood risk management is effective. However, with some exceptions such as in the Mexican government, Caribbean and Pacific island countries, ex-ante parametric risk financing at the national level is uncommon (OECD, 2011; The World Bank, 2012a). It is worth pursuing the possibility of creating a common insurance pool in Asia. Furthermore, basis risk can be addressed through the implementation of index-based derivatives (Michel-Kerjan & Morlaye, 2008; OECD, 2011). Finally, ex-ante financing tools based on the parametric index will add an additional layer to protect people against catastrophes (The World Bank, 2012a). However, due to inherent basis risk, governments and donors need to provide safety nets to those who might be negatively impacted by disasters and cannot be supported by parametric risk transfer products.

# CHAPTER 8. CONCLUSIONS AND THE FUTURE STUDY

Historically, disaster risk management community focused on hazards; however, they have realized that other factors that consist of disaster risk, i.e. exposure and vulnerability, are also critical determinants for effective risk management. If exposure and vulnerability change over time, the whole disaster risk will alter as well. High exposures of electric grids in New York City caused service disruptions of the critical infrastructure of the city during Hurricane Sandy. In addition, due to more interdependent infrastructure and the global economy, disaster risks, which used to be local, quickly propagates to other parts of the world. Because of these factors, economic burden increased drastically over the course of 100 years, while death rates from natural disasters have declined. However, current knowledge does not account for regional or global significances of these connections. Therefore, this dissertation attempted to conduct a long-term risk assessment of natural hazards, access potential losses of interdependent infrastructure and economic systems. This collectively informed a strategy for rapid response and recovery.

Chapter 2 proposed that it is essential for local policy makers to comprehensively look at these indices and rainfall intensity, volume, and duration to provide a flood prediction early-warning system in Manila. Local policy makers must consider rainfall amount and duration, type of rainfall, and vegetation indices along with other important indicators such as water height at local rivers and dams. Chapter 3 filled the gaps in technical knowledge about the recurrence probability of dzud by estimating the return levels of relevant climatic variables. The study estimated the distributions of summer drought conditions and winter minimum temperature and their return levels in Mongolia for risk analysis. Chapter 4 estimated the direct and indirect damages caused by Hurricane Sandy in each critical infrastructure sector, using GIS mapping techniques. The methodology enables a quick assessment of damages caused by interdependence in critical infrastructures. It also introduced a Bayesian network as a tool to analyze critical infrastructure interdependence. Then, in order to address SMEs and supply chain resilience, Chapter 5 proposed a new type of BCM, a regional BCM based on Public-Private Partnership (PPP), and a new role for the insurance industry. In Chapter 6, comparing different supply chains and industries’ structure in the case of Thailand’s flooding, the study identified the factors in private investment decision-making. Finally, Chapter 7 developed a flood index with single and multiple triggers for Thailand and Bangladesh to address catastrophic floods.

There are several points left for the future study. First, this thesis was the first attempt to discuss losses derived from interdependence (Chapter 4 and Chapter 5), but did not estimate or quantify losses caused by interdependences. It is critical to estimate and quantify losses caused by interdependences both in critical infrastructures and supply chains. Bayesian network has the potential to quantify the interdependences among nodes in the network. Thus, the future study should develop a supply chain model that can quantitatively assess countermeasures for supply chain or critical infrastructure vulnerability. By doing so, one can discover what kind of effective measures are available for private companies to manage supply chain disruptions caused by floods. A model using a Bayesian network can be built in the following way: i) in a static case with discrete probability distributions, ii) in a static case with continuous probability distributions, and iii) in a dynamic case with continuous distributions.

Second, utilizing the methods and results proposed by this thesis, the future study needs to improve a methodology to estimate damage and losses caused by disasters. The rapid assessment of damages and losses after disasters is critical for communities and governments to quickly move recovery and reconstruction forward. Currently, the assessments have been mainly conducted at the ground-level. Since a methodology requires existing social, economic and physical data and developing nations often lack them, it is challenging for developing nations to assess damages and losses quickly after disasters. Furthermore, recent technological development in remote sensing has potential of changing these situations. Satellite-based emergency mapping is most intensively deployed in Asia and Europe, proportionally following the geographic, physical, and temporal distributions of natural disasters (Voigt et al 2016). Remote sensing technologies could expedite the damage and loss assessment, enabling governments to quickly move forward the recovery and reconstruction phases, such as dispersing insurance payments quickly. Additionally, the IPCC (2012) argues that risk sharing and transfer mechanisms, such as insurance and catastrophic bonds can increase resilience to disasters. However, harnessing the recent development of remote sensing technologies, the current damage and loss assessment must be improved for rapid financial response after catastrophic floods. Therefore, based on rainfall and flood index proposed by this thesis, the future work should investigate how to improve VaR for private enterprises and supply chains. The work should examine how to design insurance and reinsurance industries in order to improve VaR in supply chains. The work will develop a methodology for calculating economic impacts in the business and infrastructure sectors and financial scheme for rapid response. This can address the following two questions: “How can a rapid damage assessment be improved?” and “What is a desirable insurance scheme to rapidly mobilize financial resources right after catastrophic floods?”

Third, while conducting the above studies, it is important to account for natural capital losses. Most of the calculated losses at the present dataset comes from manufactured or built capital Mutter (2015). However, natural capital, such as forests or beaches, can be damaged, but generally they are not counted as losses (Mutter, 2015). This thesis does not consider natural capital in damages and losses. Considering that remote sensing products can capture vegetation changes after disasters, future studies must quantify changes in natural capital, such as forests and beaches, monitored by remote sensing.

Finally, Chapter 3 (Risk Analysis for Dzud) and Chapter 7 (A Strategy for Parametric Flood Insurance Using Proxies) examined parametric insurance. A number of parametric insurance products have been implemented in developing nations from micro level to macro level. However, impact analysis has never been conducted for these products (Miranda & Farrin, 2012). Therefore, future studies must analyze the impacts of these parametric indexes for natural disasters.

# Bibliography


Abe, Masato, & Ye, Linghe. (2013). Building resilient supply chains against natural disasters: The cases of Japan and Thailand. *Global Business Review*, 14(4), 567-586.

Adger, W. N., Eakin, H., & Winkels, A. (2009). Nested and teleconnected vulnerabilities to environmental change. *Frontiers in Ecology and the Environment*, 7(3), 150–157. http://doi.org/10.1890/070148

Afuah, A. (2000). How much do your "co-opetitors'" capabilities matter in the face of technological change?. *Strategic Management Journal*, 387-404.

Ahn, J. H., & Choi, H. Il. (2013). A new flood index for use in evaluation of local flood severity: a case study of small ungauged catchments in Korea. *Journal of the American Water Resources Association*, 49(1), 1–14. http://doi.org/10.1111/jawr.12025

Albert, R., et al. (2004). Structural vulnerability of the North American power grid. *Physical review E,* 69(2): 025103.

Annarelli, A., & Nonino, F. (2016). Strategic and operational management of organizational resilience: Current state of research and future directions. *Omega*, *62*, 1-18.

Aon Benfield. (2012). 2011 Thailand floods event recap report: Impact forecasting. Retrieved from http://thoughtleadership.aonbenfield.com/ Documents/20120314_impact_forecasting_thailand_flood_ event_recap.pdf.

Archie III, L., & McCormack, K. (2012). Modeling supplier risks using Bayesian networks. *Industrial Management and Data Systems*, 112(2), 313-333.

Asian Development Bank. (1994, 24-27 August 1993). Managing water resources to meet megacity needs. Paper presented at the Regional Consultation Manila.

Aung, Z. and K. Watanabe (2010). Modeling inoperability propagation using bayesian networks. *Critical Infrastructure Protection IV*. T. Moore and S. Shenoi, Springer Berlin Heidelberg. 342: 199-212.

Baba, H, Watanabe, T, & Miyata, K. (2015). Area business continuity management, a new approach to sustainable local economy (Special Issue on Selected Papers from TIEMS Annual Conference in Niigata). *Journal of Disaster Research*, 10(2), 204-209.

Baba, H., & Shimano, T. (2015). 10 The role of the private sector in disaster risk management following catastrophic events. *Disaster Risk Reduction for Economic Growth and Livelihood: Investing in Resilience and Development*, 196.

Baba, Hitoshi. (2014). Introductory study on disaster risk assessment and area business continuity planning in industry agglomerated areas in the ASEAN. *IDRiM Journal*, 3(2), 184-195.

Bankoff, G. (2003). Constructing vulnerability: the historical, natural and social generation of flooding in metropolitan manila. *Disasters*, 27(3), 224–238. http://doi.org/10.1111/1467-7717.00230

Barnett, B. J., & Mahul, O. (2007). Weather index insurance for agriculture and rural areas in lower-income countries. *American Journal of Agricultural Economics*, 89(5), 1241–1247. http://doi.org/10.1111/j.1467-8276.2007.01091.x

Barnett, B. J., Barrett, C. B., & Skees, J. R. (2008). Poverty traps and index-based risk transfer products. *World Development*, 36(10), 1766–1785. http://doi.org/10.1016/j.worlddev.2007.10.016

Batima P, Natsagdorj L, Gombluudev P, & Erdenetsetseg B. (2005). Observed climate change in Mongolia. *AIACC Working Papers*. Retrieved from http://www.start.org/Projects/AIACC_Project/working_papers/Working Papers/AIACC_WP_No013.pdf

Bayasgalan, B., Mijiddorj, R., Gombluudev, P., Oyunbaatar, D., Bayasgalan, M., Tas, A., … Molomjamts, L. (2009). Climate change and sustainable livelihood of rural people in Mongolia. In: *the Adaptation Continuum: Groundwork for the Future*. ETC Foundation, Leusden, 193–213.

Begzsuren, S., Ellis, J. E., Ojima, D. S., Coughenour, M. B., & Chuluun, T. (2004). Livestock responses to droughts and severe winter weather in the Gobi Three Beauty National Park, Mongolia. *Journal of Arid Environments*, 59(4), 785–796. http://doi.org/10.1016/j.jaridenv.2004.02.001

Bell, A. R., Osgood, D. E., Cook, B. I., Anchukaitis, K. J., McCarney, G. R., Greene, A. M., … Cook, E. R. (2013). Paleoclimate histories improve access and sustainability in index insurance programs. *Global Environmental Change*, 23(4), 774–781.

Bhaskar, N. R., French, M. N., & Kyiamah, G. K. (2000). Characterization of flash floods in eastern Kentucky. *Journal of Hydrologic Engineering*, 5(3), 327–331. http://doi.org/10.1061/(ASCE)1084-0699(2000)5:3(327)

Bhattacharya, B., Islam, T., Masud, S., Suman, A., & Solomatine, D. P. (2016). The use of a flood index to characterise flooding in the north-eastern region of Bangladesh. *E3S Web of Conferences*, 7, 10003. http://doi.org/10.1051/e3sconf/20160710003

Birkmann, J., 2006: Measuring vulnerability to promote disaster-resilient societies: conceptual frameworks and definitions. In: *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies* [Birkmann, J. (ed.)]. United Nations University Press, Tokyo, Japan, pp. 9-54.

Blackhurst, J., Craighead, C.W., Elkins, D., & Handfield, R.B. (2005). An empirically derived agenda of critical research issues for managing supply-chain disruptions. *International Journal of Production Research*, 43(19), 4067-4081.

Bolgar, C. (2007). Corporate resilience comes from planning, flexibility and the creative management of risk. *The Wall Street Journal*, A12.

Bubeck, P., Botzen, W. J. W., & Aerts, J. C. J. H. (2012). A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk Analysis*, 32(9), 1481–1495. http://doi.org/10.1111/j.1539-6924.2011.01783.x

Buuren, S. van, & Groothuis-Oudshoorn, K. (2011). mice: multivariate imputation by chained equations in R. *Journal of Statistical Software*, 45(3), 1–67. http://doi.org/10.18637/jss.v045.i03

Cardona, O.D., 1999: Environmental management and disaster prevention: Two related topics: A holistic risk assessment and management approach. In: *Natural Disaster Management* [Ingleton, J. (ed.)]. IDNDR-Tudor Rose, London, UK, pp. 151-153.

Cardona, O.D., 2011: Disaster risk and vulnerability: Notions and measurement of human and environmental insecurity. In: *Coping with Global Environmental Change, Disasters and Security – Threats, Challenges, Vulnerabilities and Risks* [Brauch, H.G., U. Oswald Spring, C. Mesjasz, J. Grin, P. Kameri-Mbote, B. Chourou, P. Dunay, J. Birkmann]. Springer Verlag, Berlin, Germany, pp. 107- 122.

Carreño, M.L., O.D. Cardona, and A.H. Barbat, 2007: A disaster risk management performance index. *Journal of Natural Hazards*, 41(1), 1-20.

Carvalho, Helena, Cruz-Machado, V, & Tavares, José Guilherme. (2012). A mapping framework for assessing supply chain resilience. *International Journal of Logistics Systems and Management*, 12(3), 354-373.

Chantarat, S., Mude, A. G., Barrett, C. B., & Carter, M. R. (2013). Designing index-based livestock insurance for managing asset risk in Northern Kenya. *Journal of Risk and Insurance*, 80(1), 205–237. http://doi.org/10.1111/j.1539-6975.2012.01463.x

Cheng, L., AghaKouchak, A., Gilleland, E., Katz, R. W., Kirshen, P. H., Katz, R. W., … Katz, R. W. (2014). Non-stationary extreme value analysis in a changing climate. *Climatic Change*, 127(2), 353–369. http://doi.org/10.1007/s10584-014-1254-5

Cioffi, F., Lall, U., Rus, E., & Krishnamurthy, C. K. B. (2015). Space-time structure of extreme precipitation in Europe over the last century. *International Journal of Climatology*, 35(8), 1749–1760. http://doi.org/10.1002/joc.4116

Climate Research Unit. (n.d.). CRU ts3.23. Retrieved from http://www.cru.uea.ac.uk/data.

Coles, S. (2001). *An Introduction to Statistical Modeling of Extreme Values*. London: Springer London. http://doi.org/10.1007/978-1-4471-3675-0

Cook, E. R., Anchukaitis, K. J., Buckley, B. M., D'Arrigo, R. D., Jacoby, G. C., Wright, W. E., … Wright, W. E. (2010). Asian monsoon failure and megadrought during the last millennium. *Science*, 328(5977), 486–9. http://doi.org/10.1126/science.1185188

Croson, D. C., & Kunreuther, H. C. (2000). Customizing indemnity contracts and indexed cat bonds for natural hazard risks. *The Journal of Risk Finance*, 1(3), 24–41.

Cuomo, A. M. (2012). Governor Cuomo holds meeting with New York's congressional delegation, Mayor Bloomberg and regional county executives to review damage assessment for the State in the wake of Hurricane Sandy. Retrieved from https://www.governor.ny.gov/news/governor-cuomo-holds-meeting-new-yorks-congressional-delegation-mayor-bloomberg-and-regional

Dai, A., Trenberth, K. E., & Qian, T. (2004). A global dataset of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming. *Journal of Hydrometeorology*, 5(6), 1117–1130.

Databank, Teikoku. (2014). Higashinihon Daishinsai Karen Tosan, Hansin Daisinsai jino 3.8bai [The number of bankruptcies caused by the Great East Japan Earthquake is 3.8 times more than ones caused by Hanshin Awaji Earthquake]. In T. Databank (Ed.). Tokyo: Teikoku Databank.

Davi, N. K., D'Arrigo, R., Jacoby, G. C., Cook, E. R., Anchukaitis, K. J., Nachin, B., … Leland, C. (2015). A long-term context (931–2005 C.E.) for rapid warming over Central Asia. *Quaternary Science Reviews*, 121, 89–97. http://doi.org/10.1016/j.quascirev.2015.05.020

Davi, N., Jacoby, G., Fang, K., Li, J., D'Arrigo, R., Baatarbileg, N., & Robinson, D. (2010). Reconstructing drought variability for Mongolia based on a large-scale tree ring network: 1520–1993. *Journal of Geophysical Research*, 115(D22), D22103. http://doi.org/10.1029/2010JD013907

DeStefano, M. (2012). Bloomberg: sandy losses total $19 billion. *New York New*.

Desai, K. R. (2013). Meso-Level Flood Index Insurance Pilot in Sirajganj, Bangladesh - The Process Note.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Blöschl, G. (2013). Socio-hydrology: conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, 17(8), 3295–3303. http://doi.org/10.5194/hess-17-3295-2013

Dixon, P. B., & Rimmer, M. T. (Eds.). (2001). *Dynamic general equilibrium modelling for forecasting and policy: a practical guide and documentation of MONASH*. Emerald Group Publishing Limited.

Doherty, N. A. (1997). Financial innovation for financing and hedging catastrophe risk. *Financial Risk Management for Natural Catastrophes*, 191–209.

Doherty, N. A., & Richter, A. (2002). Moral hazard, basis risk, and gap insurance. *Journal of Risk and Insurance*, 69(1), 9–24. http://doi.org/10.1111/1539-6975.00002

Du, H., Wu, Z., Li, M., Jin, Y., Zong, S., & Meng, X. (2013). Characteristics of extreme daily minimum and maximum temperature over Northeast China, 1961–2009. *Theoretical and Applied Climatology*, 111(1–2), 161–171. http://doi.org/10.1007/s00704-012-0649-3

Du, H., Wu, Z., Zong, S., Meng, X., & Wang, L. (2013). Assessing the characteristics of extreme precipitation over northeast China using the multifractal detrended fluctuation analysis. *Journal of Geophysical Research Atmospheres*, 118(12), 6165–6174. http://doi.org/10.1002/jgrd.50487

D’Arrigo, R., Jacoby, G., Frank, D., Pederson, N., Cook, E., Buckley, B., … Dugarjav, C. (2001). 1738 years of Mongolian temperature variability inferred from a tree‐ring width chronology of Siberian pine. *Geophysical Research Letters*, 28(3), 543‐546.

Elabed, G., Bellemare, M. F., Carter, M. R., & Guirkinger, C. (2013). Managing basis risk with multiscale index insurance. *Agricultural Economics* (United Kingdom), 44(4–5), 419–431. http://doi.org/10.1111/agec.12025

Engkagul, S. (1993). Flooding features in Bangkok and vicinity: Geographical approach. *GeoJournal*, 31(4), 335-338.

FEMA Modeling Task Force(MOTF) (2013). GIS Data/MOTF/Hurricane Sandy.

FEMA Modeling Task Force(MOTF) (2013). GISData Imagery-Based_Assessments.

Fernández-Giménez, M. E., Batkhishig, B., & Batbuyan, B. (2012). Cross-boundary and cross-level dynamics increase vulnerability to severe winter disasters (dzud) in Mongolia. *Global Environmental Change*, 22(4), 836–851. http://doi.org/10.1016/j.gloenvcha.2012.07.001

Fujimoto, T. (2011). Supply chain competitiveness and robustness: A lesson from the 2011 tohoku earthquake and supply chain “virtual dualization”. *MMRC Discussion Paper Series*, 362. http://merc.e.u-tokyo.ac.jp/mmrc/dp/pdf/MMRC362_2011.pdf

Fukase, Atsuko. (2012, February 14). Thai floods sink Japanese insurers, *The Wall Street Journal*.

Gale, E. L., & Saunders, M. A. (2013). The 2011 Thailand flood: Climate causes and return periods. *Weather*, 68(9), 233–237. http://doi.org/10.1002/wea.2133

Gassebner, M., Keck, A., & Teh, R. (2010). Shaken, not stirred: The impact of disasters on international trade. *Review of International Economics*, 18(2), 351–368. http://doi.org/10.1111/j.1467-9396.2010.00868.x

Gilleland, E., & Katz, R. W. (2016). extRemes 2.0: An extreme value analysis package in R. *Journal of Statistical Software*, 72(8). Retrieved from http://www.jstatsoft.org/

Haraguchi, M., & Kim, S. (2016). Critical infrastructure interdependence in New York City during Hurricane Sandy. *International Journal of Disaster Resilience in the Built Environment*, *7*(2), 133-143.

Haraguchi, Masahiko, & Lall, Upmanu. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256-272.

Hofman, Debra, & Aronow, Stan. (2012). Measuring resiliency in the supply chain top 25. Retrieved from https://www.gartner.com/doc/1950717/measuring-resiliency-supply-chain-top.

Hopson, T. M., & Webster, P. J. (2010). A 1–10-day ensemble forecasting scheme for the major river basins of Bangladesh: forecasting severe floods of 2003–07. *Journal of Hydrometeorology*, 11(3), 618–641. http://doi.org/10.1175/2009JHM1006.1

Hruska, Joel. (2012). HDD pricewatch: higher prices are the new normal. Retrieved July 9, 2012, Retrieved from http://www.extremetech.com/computing/129874-hdd-pricewatch-higher-prices-are-the-new-normal

IPCC. 2007. *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, eds. Cambridge University Press, Cambridge, UK, 976.

Ingirige, MJB, Joness, K, & Proverbs, David. (2008). Investigating SME resilience and their adaptive capacities to extreme weather events: A literature review and synthesis. Retrieved from http://usir.salford.ac.uk/18262/

International Organization for Standardization. (2012). *ISO 22301:2012(E) "Societal security – Business continuity management systems ‐ Requirements"*. International Organization for Standardization, Editor 2012.

Islam, A. S., Haque, A., & Bala, S. K. (2010). Hydrologic characteristics of floods in Ganges–Brahmaputra–Meghna (GBM) delta. *Natural Hazards*, 54(3), 797–811. http://doi.org/10.1007/s11069-010-9504-y

Islam, K. M. N. (2005). Flood loss potentials in non-agricultural sectors: assessment methods and standard loss database for Bangladesh. Dhaka: Palok Publisher.

JETRO. (2011). Tokushu Thai Kozui Fuko ni Kansuru Jyoho [Feature: Information updates regarding recovery from Thai floods]. Retrieved July 31st, 2013, from http://www.jetro.go.jp/world/asia/th/flood/complex.html

JETRO. (2012a). Keizai Doko-Thai [Economic Trends in Thailand]. Retrieved from http://www.jetro.go.jp/world/asia/th/basic_03/.

JETRO. (2012b). Thai daikozui ni kansuru hisai kigyo anket chosa kekka no kohyo ni tsuite [Results of Surveys from Companies Damaged by "the Great Flooding in Thailand"]. Bangkok, Thailand: Retrieved from http://www.jetro.go.jp/news/announcement/20120203731-news/result.pdf.

Jensen, F. V. (1996). *An introduction to Bayesian networks*, UCL press London.

Jensen, F.V., & Nielsen, T.D. (2007). *Bayesian networks and decision graphs*: Springer Verlag.

Johnson, D. A., Sheehy, D. P., Miller, D., & Damiran, D. (2006). Mongolian rangelands in transition. Science et Changements planétaires/Sécheresse, 17(1), 133–141.

Jonkman, S. N., Bočkarjova, M., Kok, M., & Bernardini, P. (2008). Integrated hydrodynamic and economic modelling of flood damage in the Netherlands. *Ecological Economics*, 66(1), 77-90. doi: 10.1016/j.ecolecon.2007.12.022

Kajitani, Y. and H. Tatano (2014). Estimation of production capacity loss rate after the great east japan earthquake and tsunami in 2011. *Economic Systems Research* 26(1): 13-38.

Kamata, Keisuke. (2012, March 9, 2012). 11nen no shinsha hanbai, shinsai to kozui de gensho, Philippines [The sales of new automobiles have decreased due to the Great East Japan Earthquake and Thailand's floods in Philippines], Tsushokoho

Katz, R. W. (2013). Statistical methods for nonstationary extremes. In *Extremes in a changing climate* (pp. 15-37). Springer, Dordrecht.

Katz, R. W., Parlange, M. B., & Naveau, P. (2002). Statistics of extremes in hydrology. *Advances in Water Resources*, 25(8–12), 1287–1304. http://doi.org/10.1016/S0309-1708(02)00056-8

Kendall, M. G. (1948). *Rank correlation methods*.

Khalil, A. F., Kwon, H.-H., Lall, U., Miranda, M. J., & Skees, J. (2007). El Nino-Southern Oscillation-based index insurance for floods: Statistical risk analyses and application to peru. *Water Resources Research*, 43(10), n/a-n/a. http://doi.org/10.1029/2006WR005281

Kinney, R., et al. (2005). "Modeling cascading failures in the North American power grid." *The European Physical Journal B - Condensed Matter and Complex Systems* 46(1): 101-107.

Kleindorfer, P. R. (2009). Climate change and insurance: integrative principles and regulatory risks. *INSEAD Working Paper Series*, 22. article. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1456862\nfile:///R:/LITERATURE/Chris/Gassman Insurance FONTAINEBleu.doc.pdf

Kleindorfer, Paul R, & Saad, Germaine H. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, 14(1), 53-68.

Komori, Daisuke, Nakamura, Shinichirou, Kiguchi, Masashi, Nishijima, Asako, Yamazaki, Dai, Suzuki, Satoshi, . . . Oki, Taikan. (2012). Characteristics of the 2011 Chao Phraya River flood in Central Thailand. *Hydrological Research Letters*, 6, 41-46. http://doi.org/10.3178/HRL.6.41

Kuhlicke, C., Scolobig, A., Tapsell, S., Steinführer, A., & De Marchi, B. (2011). Contextualizing social vulnerability: findings from case studies across Europe. *Natural Hazards*, 58(2), 789–810. article. http://doi.org/10.1007/s11069-011-9751-6

Kunz, M., Mühr, B., Kunz-Plapp, T., Daniell, J. E., Khazai, B., Wenzel, F., . . . Zschau, J. (2013). Investigation of Superstorm Sandy 2012 in a multi-disciplinary approach. *Natural Hazards and Earth System Sciences*, 1(2), 625-679. doi: 10.5194/nhessd-1-625-2013

Kushima, Mayumi. (2012). Shinsai norikoe kokunai shijo ni keisha suru kanan jidousha sangyo [Automobile industry that focuses on the domestic market after overcoming the challenges caused by Japanese earthquake]. Retrieved from http://www.hkpost.com.hk/index2.asp?id=3036

Lall, U., Ceccato, P., Allaire, M. C., Cian, F., & Haraguchi, M. (2017). The Project Report.

Lall, U., Devineni, N., & Kaheil, Y. (2016). An empirical, nonparametric simulator for multivariate random variables with differing marginal densities and nonlinear dependence with hydroclimatic applications. *Risk Analysis*, 36(1), 57–73.

Lazzarini, S.G., Chaddad, F.R., & Cook, M.L. (2001). Integrating supply chain and network analyses: the study of netchains. *Journal on chain and network science*, 1(1), 7-22.

Lebel, L., Manuta, J.B., & Garden, P. (2011). Institutional traps and vulnerability to changes in climate and flood regimes in Thailand. *Regional Environmental Change*, 11(1), 45-58.

Leontief, W. (1986). *Input output economics*, Oxford University Press.

Linnerooth-Bayer, J., & Sjostedt, G. (2010). *Transboundary risk management*. Routledge.

Liu, Y. Y., Evans, J. P., McCabe, M. F., de Jeu, R. A. M., van Dijk, A. I. J. M., Dolman, A. J., & Saizen, I. (2013). Changing climate and overgrazing are decimating Mongolian steppes. *PLoS ONE*, 8(2), e57599. http://doi.org/10.1371/journal.pone.0057599

Liverman, Diana. (2015). US National climate assessment gaps and research needs: overview, the economy and the international context. *Climatic Change*, 1-14.

Lockamy III, A., & McCormack, K. (2010). Analysing risks in supply networks to facilitate outsourcing decisions. *International Journal of Production Research*, 48(2), 593-611.

Lu, M., Lall, U., Schwartz, A., & Kwon, H. (2013). Precipitation predictability associated with tropical moisture exports and circulation patterns for a major flood in France in 1995. *Water Resources Research*, 49(10), 6381–6392.

METI. (2011). Emergency Survey on Supply Chain Restoration Damaged by the Flood in Thailand. Retrieved from http://www.meti.go.jp/english/press/2011/1221_02.html.

METI. (2012). White Paper on International Economy and Trade 2012. Tokyo Japan: Retrieved from http://www.meti.go.jp/english/report/data/gIT2012maine.html.

MacKenzie, Cameron A., Santos, Joost R., & Barker, Kash. (2012). Measuring changes in international production from a disruption: Case study of the Japanese earthquake and tsunami. *International Journal of Production Economics*, 138(2), 298-302. doi: 10.1016/j.ijpe.2012.03.032

Mahul, O., & Skees, J. R. (2007). Managing agricultural risk at the country level: The case of index-based livestock insurance in Mongolia. *World Bank Working Paper,* 4325. The World Bank.

Mahul, O., & Stutley, C. J. (2010). Government support to agricultural insurance: challenges and options for developing countries. World Bank Publications.

Mahul, O., Belete, N., & Goodland, A. (2009). Innovations in insuring the poor: Index-based livestock insurance in Mongolia (2020 Vision Focus Brief). Washington DC, U.S.: Washington, DC.

Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica: Journal of the Econometric Society*, 245–259.

McSharry, P. (2014). The role of scientific modelling and insurance in providing innovative solutions for managing the risk of natural disasters. In *Reducing Disaster: Early Warning Systems for Climate Change* (pp. 325–338). Springer.

Mckee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Eighth Conference on Applied Climatology*, 17–22. Retrieved from http://ccc.atmos.colostate.edu/relationshipofdroughtfrequency.pdf

Mechler, R, Linnerooth-Bayer, J, Hochrainer, S, Pflug, G, & Pflug, G. (2006). Assessing financial vulnerability and coping capacity: the IIASA CATSIM model. *Measuring vulnerability and coping capacity to hazards of natural origin. Concepts and methods*. United Nations University Press, Tokyo, 380-398.

Merz, B, Vorogushyn, S, Lall, U, Viglione, A, & Blöschl, G. (2015). Charting unknown waters—On the role of surprise in flood risk assessment and management. *Water Resources Research*, 51(8), 6399-6416.

Merz, B., Aerts, J., Arnbjerg-Nielsen, K., Baldi, M., Becker, A., Bichet, A., … Nied, M. (2014). Floods and climate: emerging perspectives for flood risk assessment and management. *Natural Hazards and Earth System Science*, 14(7), 1921–1942. http://doi.org/10.5194/nhess-14-1921-2014

Michel-Kerjan, E., & Morlaye, F. (2008). Extreme events, global warming, and insurance-linked securities: how to trigger the "tipping point." *The Geneva Papers on Risk and Insurance - Issues and Practice*, 33(1), 153–176. http://doi.org/10.1057/palgrave.gpp.2510159

Middleton, N., Rueff, H., Sternberg, T., Batbuyan, B., & Thomas, D. (2015). Explaining spatial variations in climate hazard impacts in western Mongolia. *Landscape Ecology*, 30(1), 91–107. http://doi.org/10.1007/s10980-014-0091-2

Ministry of Economy Trade and Industry. (2011). Daishinsaigo no nihon keizai wo meguru genjo to kadai [situations and challenges of the Japanese economy after the great earthquake]. Tokyo: Ministry of Economy Trade and Industry, Retrieved from http://www.meti.go.jp/committee/summary/0004660/23_007_05_00.pdf.

Miranda, M. J., & Farrin, K. (2012). Index insurance for developing countries. *Applied Economic Perspectives and Policy*, 34(3), 391–427. http://doi.org/10.1093/aepp/pps031

Mirza, M. M. Q. (2003). Three recent extreme floods in bangladesh: a hydro-meteorological analysis. *Natural Hazards*, 28(1), 35–64. http://doi.org/10.1007/978-94-017-0137-2_2

Mitsubishi UFJ Research and Consulting. (2012). Chusho kigyou no risk management ni kansuru chosa ni kakaru itaku jigyou [a commissioned project on the study that investigates risk management in small and medium enterprises]. Tokyo: Retrieved from http://www.meti.go.jp/meti_lib/report/2012fy/0025056.pdf.

More, Dileep, & Subash Babu, A. (2008). Perspectives, practices and future of supply chain flexibility. *International Journal of Business Excellence*, 1(3), 302-336.

Mori, M., Watanabe, M., Shiogama, H., Inoue, J., & Kimoto, M. (2014). Robust Arctic sea-ice influence on the frequent Eurasian cold winters in past decades. *Nature Geoscience*, 7(12), 869–873. http://doi.org/10.1038/ngeo2277

Morinaga, Y., Tian, S.-F., & Shinoda, M. (2003). Winter snow anomaly and atmospheric circulation in Mongolia. *International Journal of Climatology*, 23(13), 1627–1636. http://doi.org/10.1002/joc.961

Motter, A. E. and Y.-C. Lai (2002). "Cascade-based attacks on complex networks." *Physical review E* 66(6): 065102.

Mukhopadhyay, A., Chatterjee, S., Saha, D., Mahanti, A., & Sadhukhan, S. K. (2006, January). e-Risk management with insurance: A framework using copula aided Bayesian belief networks. In *System Sciences, 2006. HICSS'06. Proceedings of the 39th Annual Hawaii International Conference on* (Vol. 6, pp. 126a-126a). IEEE.

Munich Re. (2012). *Topics Geo Natural Catastrophes 2011*. Retrieved July 10, 2012, from www.munichre.com/publications/302-07225_en.pdf

Munich Re. 2013a. Münchener Rückversicherungs-Gesellschaft, *Geo Risks Research*, NatCatSERVICE. Retrieved from http://www.munichre.com/en/reinsurance/business/non-life/georisks/natcatservice/default.aspx

Munich Re. 2013b. Information portal. https://www.munichre.com/touch/portal/en/6

Muto, M., Morishita, K., & Syson, L. (2012). Impacts of climate change upon Asian coastal areas: the case of metro Manila. *Climate Change Adaptation and International Development: Making Development Cooperation More Effective*, 67.

Mutter, J. C. (2015). *The Disaster Profiteers: How Natural Disasters Make the Rich Richer and the Poor Even Poorer*. Macmillan.

Müller, M., Kašpar, M., Valeriánová, A., Crhová, L., Holtanová, E., & Gvoždíková, B. (2015). Novel indices for the comparison of precipitation extremes and floods: an example from the Czech territory. *Hydrology and Earth System Sciences*, 19(11), 4641–4652. http://doi.org/10.5194/hess-19-4641-2015

NKSJ Risk Management. (2012). Heisei 23 Nendo Chushokigyo Jigyokeizokukeikaku Ni Kansuru Chosa [Study on Business Continuity Planning of Small and Medium Enterprises]. Tokyo: Retrieved from http://www.meti.go.jp/meti_lib/report/2012fy/E002556.pdf.

NYS GIS Clearinghouse (2013).

Nakamura, J., Lall, U., Kushnir, Y., Robertson, A. W., & Seager, R. (2013). Dynamical structure of extreme floods in the US Midwest and the United Kingdom. *Journal of Hydrometeorology*, 14(2), 485–504.

National Centers for Environmental Information, N. (n.d.). Monsoon Asia Drought Atlas (MADA). Retrieved July 10, 2017, from https://www.ncdc.noaa.gov/paleo-search/study/10435

National Research Council. (2011). *Building Community Disaster Resilience Through Private-Public Collaboration*: National Academies Press.

Natsagdorj, L., & Dulamsuren, J. (2001). Some aspects of assessment of the dzud phenomena. *Papers in Meteorology and Hydrology*, 23, 3–18.

Nell, M., & Richter, A. (2000). Catastrophe index-linked securities and reinsurance as substituties. *Working Paper Series: Finance & Accounting*, Johann Wolfgang Goethe-Universität Frankfurt a. M.

New York City Government (2012). New York City Selected Facilities and Program Sites 2005. New York, USA.

New York City Government (2013). *NYC PlaNYC: A Stronger, More resilient New York*.

Noy, Ilan. (2015). Comparing the direct human impact of natural disasters for two cases in 2011: The Christchurch earthquake and the Bangkok flood. *International Journal of Disaster Risk Reduction*, 13, 61-65.

Nutalaya, P., Yong, R. N., Chumnankit, T., & Buapeng, S. (1996). Land subsidence in Bangkok during 1978–1988. In: *Sea-level rise and coastal subsidence* (pp. 105-130). Springer, Dordrecht.

O'Connor, John. (2009). Innovating through supply chain risk management. Paper presented at the 94th Annual International Supply Management Conference.

OECD. (2011). Overview and analysis of cat-linked securities. In *Risk Awareness, Capital Markets and Catastrophic Risks*. Paris, France. http://doi.org/http://dx.doi.org/10.1787/9789264046603-12-en

Okuyama, Y. (2007). "Economic modeling for disaster impact analysis: past, present, and future." *Economic Systems Research*, 19(2): 115-124.

Ozaki, M. (2016). *Disaster risk Financing in Bangladesh*. Retrieved from https://www.adb.org/sites/default/files/publication/198561/sawp-046.pdf

Pai, R. R., Kallepalli, V. R., Caudill, R. J., & Zhou, M. (2003, October). Methods toward supply chain risk analysis. In *Systems, Man and Cybernetics, 2003. IEEE International Conference on* (Vol. 5, pp. 4560-4565). IEEE.

Palmer, W. C. (1965). *Meteorological drought* (Vol. 30). Washington, DC: US Department of Commerce, Weather Bureau.

Pathak, S.D., Day, J.M., Nair, A., Sawaya, W.J., & Kristal, M.M. (2007). Complexity and adaptivity in supply networks: building supply network theory using a complex adaptive systems perspective. *Decision Sciences*, 38(4), 547-580.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference*: Morgan Kaufmann.

Penning-Rowsell, E., Johnson, C., Tunstall, S., Tapsell, S., Mor-ris, J., Chatterton, J., and Green, C. *The Benefits of Flood and Coastal Risk Management: A Manual of Assessment Techniques*, Middlesex Univ. Press, UK, 2005.

Perwaiz, A. (2015). Thailand floods and impact on private sector. In: *Disaster Management and Private Sectors* (pp. 231-245). Springer, Tokyo.

Petts, Judith. (1998). Environmental responsiveness, individuals and organizational learning: SME experience. *Journal of Environmental Planning and Management*, 41(6), 711-730.

Radisch, J. G., Catherine (2013). Interconnected, inter-dependent risk: Input paper for Thematic Research Area 16.

Ramnarong, V. (1999). Evaluation of groundwater management in Bangkok: positive and negative. *International Contributions to Hydrogeology*, 21, 51-62.

Rao, M. P., Davi, N. K., D'Arrigo, R. D., Skees, J., Nachin, B., Leland, C., … Byambasuren, O. (2015). Dzuds, droughts, and livestock mortality in Mongolia. *Environmental Research Letters*, 10(10), 74012–74012. http://doi.org/10.1088/1748-9326/10/7/074012

Reading, R. P., Bedunah, D. J., & Amgalanbaatar, S. (2006). Conserving biodiversity on Mongolian rangelands: implications for protected area development and pastoral uses. *USDA Forest Service Proceedings RMRS-P-39* [Available at: http://www.fs.fed. us/rm/pubs/rmrs_p039/rmrs_p039_001_017.pdf].

Reitman, Valerie. (1997, May 8 1997). Toyota Motor shows its mettle after fire destroys parts plant, *The Wall Street Journal.*

ReliefWeb. (2010). Mongolia: Severe Winter—Dzud. (Jun 2010). Retrieved from https://reliefweb.int/sites/reliefweb.int/files/resources/4E597847D9F7CD5685257751007620DC-SS-2010-MNG_0623.pdf

Renesas Electronics. (2011). Renesas Electronics Announces Schedule for the Resumption of Operation at the Naka Factory [Press release]. Retrieved July 10, 2012, from http://am.renesas.com/press/news/2011/news20110422.jsp

Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B. L., Mortimore, M., Batterbury, S. P. J., … Herrick, J. E. (2007). Global desertification: building a science for dryland development. *Science*, 316(5826), 847–851.

Rinaldi, S. M., et al. (2001). "Identifying, understanding, and analyzing critical infrastructure interdependencies." *Control Systems, IEEE* 21(6): 11-25.

Robbins, D Keith, Pantuosco, Louis J, Parker, Darrell F, & Fuller, Barbara K. (2000). An empirical assessment of the contribution of small business employment to US State economic performance. *Small Business Economics*, 15(4), 293-302.

Rootzén, H., & Katz, R. W. (2013). Design life level: Quantifying risk in a changing climate. *Water Resources Research*, 49(9), 5964–5972. http://doi.org/10.1002/wrcr.20425

Rose, A. (2004). Economic principles, issues, and research priorities in hazard loss estimation. *Modeling Spatial and Economic Impacts of Disasters*, 13-36.

Rose, A., & Huyck, C. K. (2016). Improving catastrophe modeling for business interruption insurance needs. *Risk analysis*, 36(10), 1896-1915.

Rose, Adam. (2004). Defining and measuring economic resilience to disasters. *An International Journal of Disaster Prevention and Management*, 13(4), 307-314.

Rose, Adam. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards*, 7(4), 383-398.

Runyan, Rodney C. (2006). Small business in the face of crisis: Identifying barriers to recovery from a natural disaster. *Journal of Contingencies and Crisis Management*, 14(1), 12-26.

Sarmiento, J. P., Hoberman, G., Ilcheva, M., Asgary, A., Majano, A. M., Poggione, S., & Duran, L. R. (2015). Private sector and disaster risk reduction: The cases of Bogota, Miami, Kingston, San Jose, Santiago, and Vancouver. *International Journal of Disaster Risk Reduction*, *14*, 225-237.

Satumtira, G. and L. Dueñas-Osorio (2010). Synthesis of modeling and simulation methods on critical infrastructure interdependencies research. *Sustainable and Resilient Critical Infrastructure Systems*, Springer: 1-51.

Savage, Mick. (2002). Business continuity planning. *Work study*, 51(5), 254-261.

Sheffi, Yossi, & Rice Jr, James B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review*, 47(1).

Sheffi, Yossi. (2005). *The resilient enterprise: overcoming vulnerability for competitive advantage*. MIT Press Books, 1.

Simchi-Levi, David. (2012). Operations rules for driving business value & growth: part 1, mitigating business risks from the known-unknown to the unknown-unknown. Retrieved from The Supply Chain Digest website: http://www.sctvchannel.com/webinars/videocast3.php?cid=5541

Sittipunt, Chadchart. (2012). Water Management Plans and Flood Prevention Measures for Industrial Zone.

Skees, J. R., & Enkh-Amgalan, A. (2002). Examining the feasibility of livestock insurance in Mongolia. *World Bank Working Paper Series*. Vol. 2886.

Sousounis, Peter. (2012). The 2011 Thai floods: Changing the perception of risk in Thailand. In M. Phelan (Ed.), *AIR Currents*.

Stevenson, Mark, & Spring, Martin. (2007). Flexibility from a supply chain perspective: definition and review. *International Journal of Operations & Production Management*, 27(7), 685-713.

Steyer, Véronique, & Gilbert, Claude. (2013). Exploring the ambiguous consensus on public–private partnerships in collective risk preparation. *Sociology of Health & Illness*, 35(2), 292-303.

Storey, David J. (1994). *Understanding the small business sector*: Cengage Learning EMEA.

Sukegawa, Seiya. (2012, June 15th). Nikkeikigyo no ooi SahaRattananakorn Industrial Estate ha teibokoji ga tetsukazu [Levee construction in SahaRattananakorn Industrial Estate, which many Japanese firms are located, has not started yet], *Tsusho Koho*. Retrieved from http://www.jetro.go.jp/world/asia/th/biznews/4fd987482f1e8

Sullivan-Taylor, Bridgette, & Branicki, Layla. (2011). Creating resilient SMEs: why one size might not fit all. *International Journal of Production Research*, 49(18), 5565-5579.

Tachiiri, K., Shinoda, M., Klinkenberg, B., & Morinaga, Y. (2008). Assessing Mongolian snow disaster risk using livestock and satellite data. *Journal of Arid Environments*, 72(12), 2251–2263.

Takahashi, Yoshio. (2012, March 7). Lessons learned: Japanese car makers a year after quake, WSJ Blogs, *The Wall Street Journal*. Retrieved from http://blogs.wsj.com/drivers-seat/2012/03/07/lessons-learned-japanese-car-makers-a-year-after-quake/?mod=google_news_blog

Teuteberg, F. (2008). Supply chain risk management: A neural network approach. *Strategies and Tactics in Supply Chain Event Management*, 99-118.

The Economist, Counting the cost of calamities, in *The Economist*. 2012: Rotterdam, Netherlands and Washington, DC. Retrieved from http://www.economist.com/node/21542755

The Government of Thailand. (2011). 24/7 Emergency Operation Center for Flood, Storms and Landslide. Retrieved from http://disaster.go.th/dpm/flood/floodEng.html.

The UN General Assembly. (2015). Sendai Framework for Disaster Risk Reduction 2015 - 2030 Sendai, Japan.

The World Bank. (2010). *Climate Risks and Adaptation in Asian Coastal Megacities*. Washington DC, U.S.

The World Bank. (2011, December 31). the World Bank supports Thailand's post-floods recovery effort. Retrieved July 10, 2012, from http://go.worldbank.org/1FYZRPKI60

The World Bank. (2012a). Improving the assessment of disaster risks to strengthen financial resilience. Washington DC, U.S. Retrieved from http://documents.worldbank.org/curated/en/606131468149390170/Improving-the-assessment-of-disaster-risks-to-strengthen-financial-resilience

The World Bank. (2012b). *Thai flood 2011: Rapid assessment for resilient recovery and reconstruction planning*. Washington DC, U.S. Retrieved from http://go.worldbank.org/1FYZRPKI60

The World Bank. (2013). *Building Resilience: Integrating Climate and Disaster Risk into Development*.

Tibken, Shara. (2012). 2nd UPDATE: Western Digital's profits fall, but co sees recovery, *The Wall Street Journal*. Retrieved from http://online.wsj.com/article/BT-CO-20120123-712851.html

Tobin, G. A. (1995). The levee love affair: a stormy relationship? *Journal of the American Water Resources Association*, 31(3), 359–367. http://doi.org/10.1111/j.1752-1688.1995.tb04025.x

Tokyo Shoko Research. (2015). "Shinsai Kara Yonen" Higashinihon Daishinsai Karen Tosan Fusaisougaku 1cho5,381oku En ["4 Years after the earthquake" Bankruptcies caused by the Great East Japan Earthquake costs indebtedness of 1 Trillion 538.1 Billion Japanese Yen]

U.S. Department of Energy (2012). Hurricane Sandy Situation Report # 19.

U.S. Department of Energy (2013). Comparing the Impacts of Northeast Hurricanes on Energy Infrastructure.

UNISDR 2011 *Global Assessment Report on Disaster Risk Reduction*. Revealing Risk, Redefining Development (Geneva: United Nations International Strategy for Disaster Reduction Secretariat)

UNISDR. (2012). Towards a Post-2015 Framework for Disaster Risk Reduction. Retrieved July 10, 2012, from http://www.unisdr.org/we/inform/publications/25129

UNISDR. (2013). *Global assessment report on disaster risk reduction 2013: From shared risk to shared value: The business case for disaster risk reduction*. United Nations.

UNISDR. (2015). *Global assessment report on disaster risk reduction 2015: Making development sustainable: The future of disaster risk management.*

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative science quarterly*, 35-67.

Venclova, K, Urbancova, H, & Vydrova, H Vostra. (2013). Advantages and disadvantages of business continuity management. Paper presented at the Proceedings of World Academy of Science, Engineering and Technology.

Vilches, Jose. (2012). HDD Pricewatch: Three Months into the Thai Floods. *Techspot.* Retrieved from http://www.techspot.com/guides/494-hard-drive-pricewatch-thai-floods

Wagner, Stephan M., & Bode, Christoph. (2006). An empirical investigation into supply chain vulnerability. *Journal of Purchasing and Supply Management*, 12(6), 301-312. doi: 10.1016/j.pursup.2007.01.004

Ward, P. J., Jongman, B., Weiland, F. S., Bouwman, A., van Beek, R., Bierkens, M. F. P., … Winsemius, H. C. (2013). Assessing flood risk at the global scale: Model setup, results, and sensitivity. *Environmental Research Letters*, 8(4), 44019. http://doi.org/10.1088/1748-9326/8/4/044019

Watanabe, Kenji. (2009). Developing public–private partnership based business continuity management for increased community resilience. *Journal of Business Continuity & Emergency Planning*, 3(4), 335-344.

Watanabe, Kenji. (2015). Regional business continuity management through public-private partnerships in *Japan Natural Disaster Management in the Asia-Pacific* (pp. 159-173): Springer.

Wei, H., et al. (2010). Inoperability input ‐ output modeling (IIM) of disruptions to supply chain networks. *Systems Engineering* 13(4): 324-339.

Wright, J. Nils. (2012, January 1). Insurance capacity shrinks after Thai floods - Reinsurers pull back as businesses struggle to quantify losses. Retrieved July 10th, 2012, from http://www.businessinsurance.com/article/20120101/NEWS04/301019977?tags=|306|64.

Wu, H., Hayes, M. J., Weiss, A., & Hu, Q. (2001). An evaluation the standardized precipitation index, the china-z index and the statistical z- score. *International Journal of Climatology*, 758(May), 745–758. http://doi.org/10.1002/joc.658

Yang, Y. C. E., Ray, P. A., Brown, C. M., Khalil, A. F., & Yu, W. H. (2014). Estimation of flood damage functions for river basin planning: a case study in Bangladesh. *Natural Hazards*, 75(3), 2773–2791. http://doi.org/10.1007/s11069-014-1459-y

Yoshida, Kaori, & Deyle, Robert E. (2005). Determinants of small business hazard mitigation. *Natural Hazards Review*, 6(1), 1-12.

Zhang, Fang. (2012). Thailand flooding helps Seagate move into first place in hard drive market in fourth quarter. Retrieved from http://www.isuppli.com/Memory-and-Storage/News/Pages/Thailand-Flooding-Helps-Seagate-Move-in-to-First-Place-in-Hard-Drive-Market-in-Fourth-Quarter.aspx

Ziegler, A.D., Lim, H.S., Jachowski, N.R., & Wasson, R. (2012). Floods, false hope, and the future. *Hydrological Processes*.

Zsidisin, George A, Melnyk, Steven A, & Ragatz, Gary L. (2005). An institutional theory perspective of business continuity planning for purchasing and supply management. *International Journal of Production Research*, 43(16), 3401-3420.

Zurich Financial Services Group and Business Continuity Institute. (2011). *Supply Chain Resilience 2011 Study*. Retrieved from http://www.zurich.com/internet/main/sitecollectiondocuments/insight/supply-chain-survey-2011.pdf

de Oliveira Teixeira, Eduardo, & Werther, William B. (2013). Resilience: Continuous renewal of competitive advantages. *Business Horizons*, 56(3), 333-342.

# Appendices

## Appendix A

Table A-1: Summary of Data Used in This Study

| | Type of Data | Number of data | Location |
|---|---|---|---|
| Flood occurrence | Binary | 7 | Dartmouth Flood Observatory.[20] |
| Rainfall Amount : Ground station | Numerical | 365 (days) x3 (years) x22 (stations) = 24090 | *NOAA NCDC GHCN v2beta* station precipitation dataset[21] |
| Rainfall Amount :CMORPH | Numerical | 365 (days) x3 (years) = 1095 | NOAA |
| Rainfall Amount :TRMM | Numerical | 365 (days) x3 (years) = 1095 | NOAA |
| Rainfall Type | Binary (Tropical cyclone or not) | 365 (days) x3 (years) = 1095 | UNISYS[22] |
| Vegetation Indices: NDVI | Numerical | 52 weeks x 3 (years) = 156 | USGS .LandDAAC .MODIS .version_005 .SEAS .reflectance. |

[20] http://www.dartmouth.edu/~floods/Archives/index.html
[21] http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.GHCN/
[22] http://weather.unisys.com/hurricane/index.php

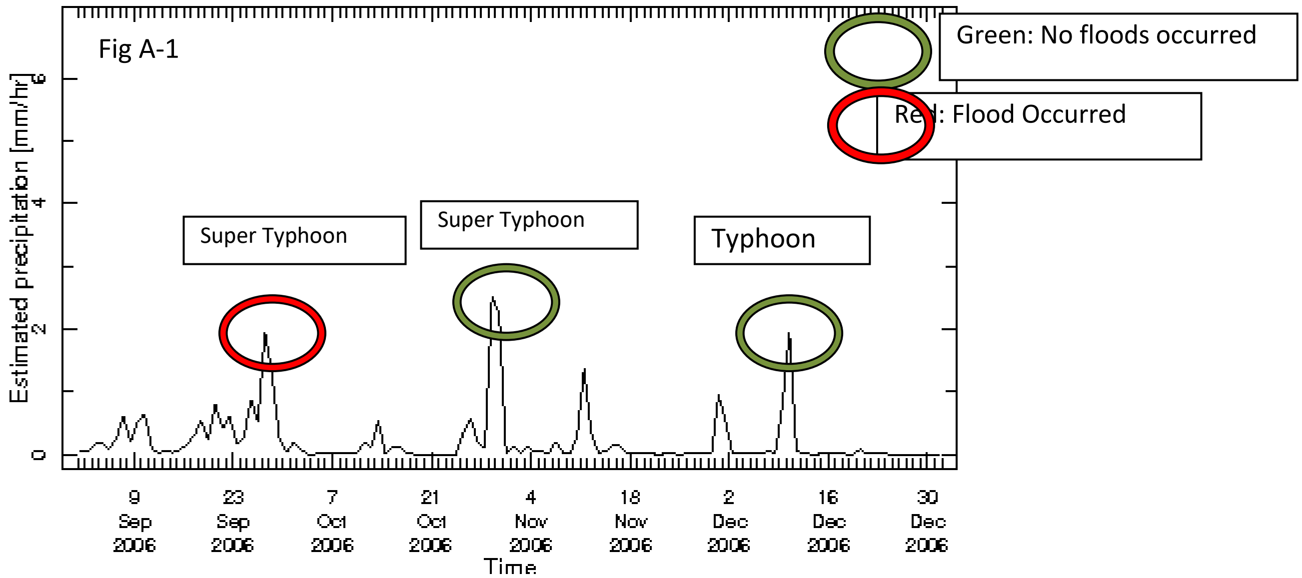


Fig A-1
Green: No floods occurred
Red: Flood Occurred
Super Typhoon
Super Typhoon
Typhoon
Estimated precipitation [mm/hr]
0
2
4
6
9 Sep 2006
23 Sep 2006
7 Oct 2006
21 Oct 2006
4 Nov 2006
18 Nov 2006
2 Dec 2006
16 Dec 2006
30 Dec 2006
Time

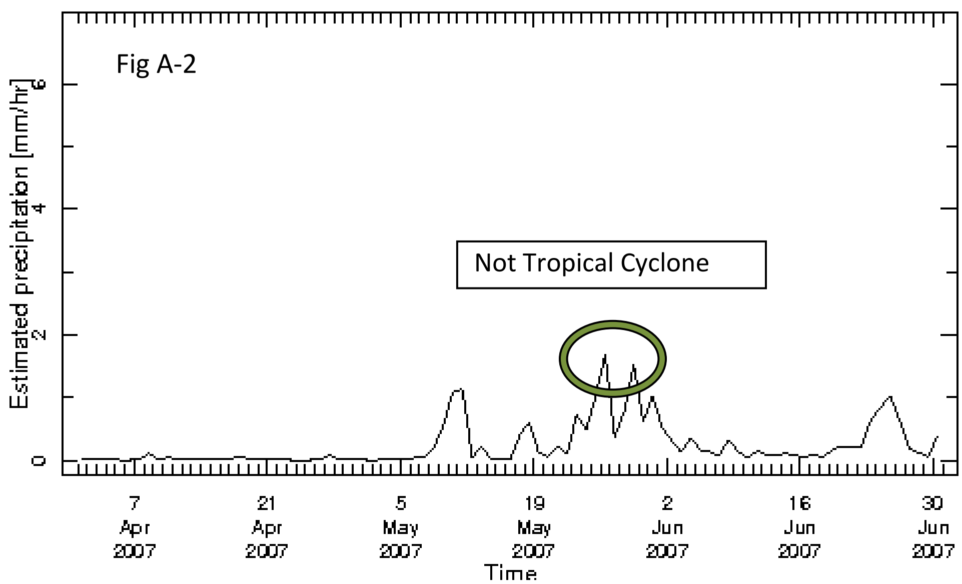



Fig A-2
Not Tropical Cyclone
Estimated precipitation [mm/hr]
0
2
4
6
7 Apr 2007
21 Apr 2007
5 May 2007
19 May 2007
2 Jun 2007
16 Jun 2007
30 Jun 2007
Time

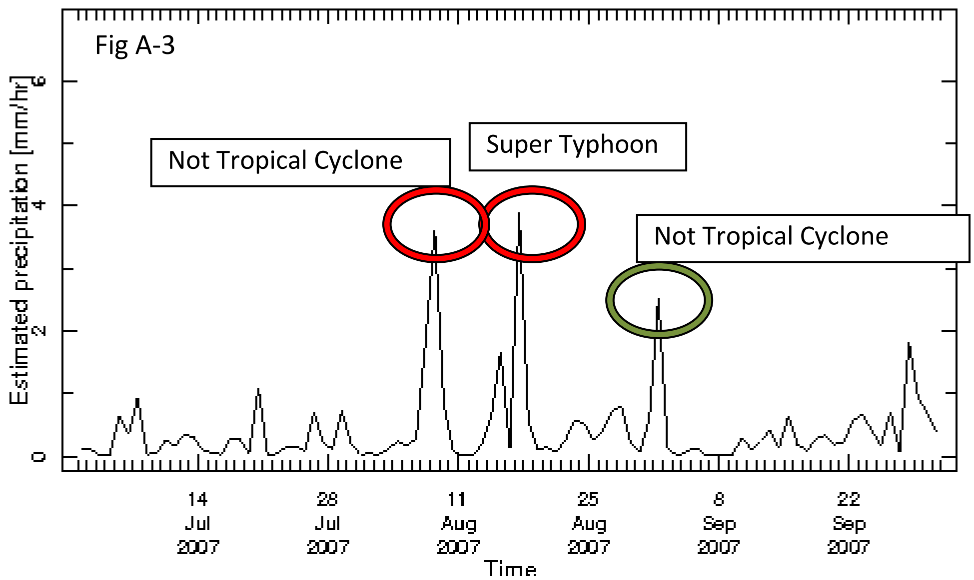


Fig A-3
Not Tropical Cyclone
Super Typhoon
Not Tropical Cyclone
Estimated precipitation [mm/hr]
0
2
4
6
14 Jul 2007
28 Jul 2007
11 Aug 2007
25 Aug 2007
8 Sep 2007
22 Sep 2007
Time

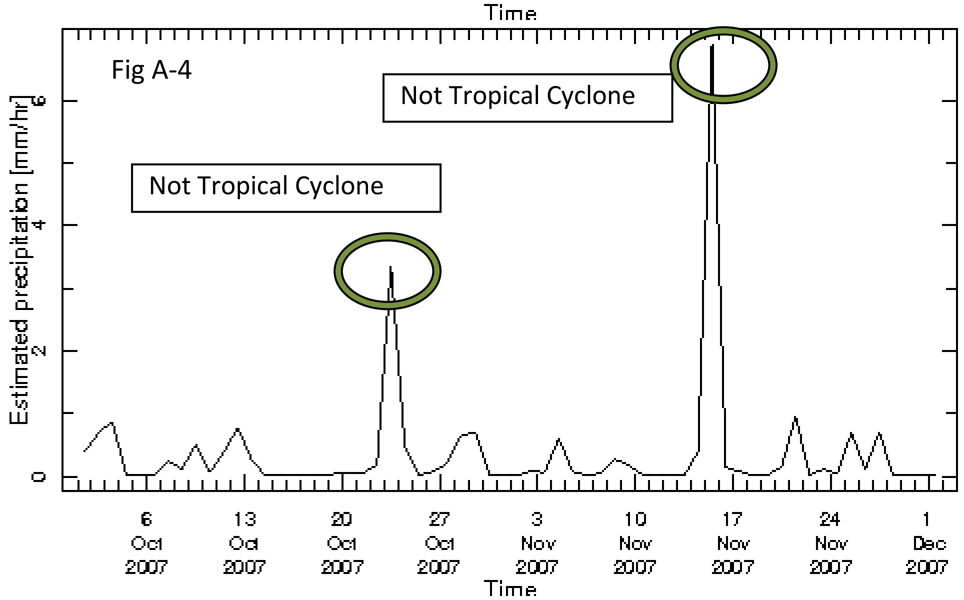


Fig A-4
Not Tropical Cyclone
Not Tropical Cyclone
Estimated precipitation [mm/hr]
0
2
4
6
6 Oct 2007
13 Oct 2007
20 Oct 2007
27 Oct 2007
3 Nov 2007
10 Nov 2007
17 Nov 2007
24 Nov 2007
1 Dec 2007
Time

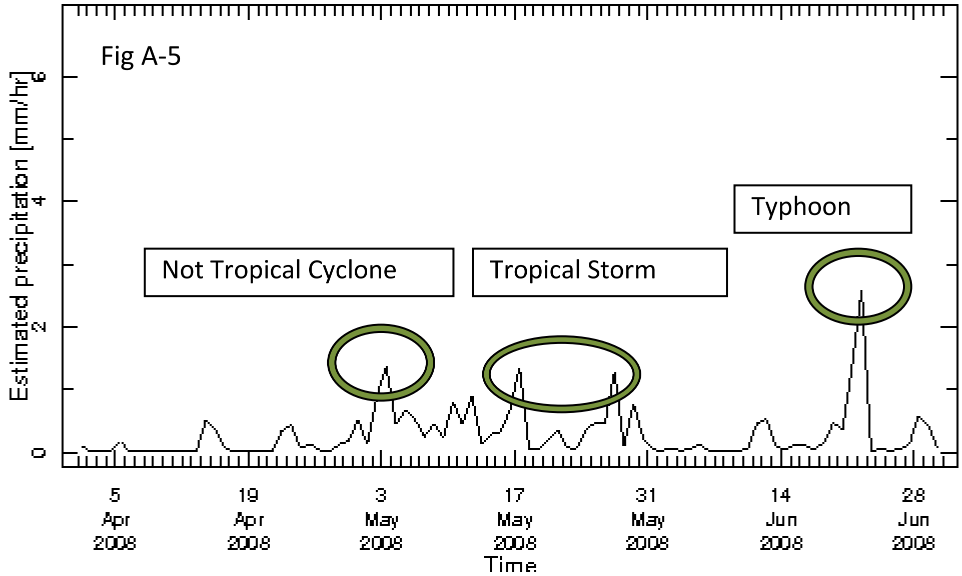


Fig A-5
Estimated precipitation [mm/hr]
0
2
4
6
Not Tropical Cyclone
Tropical Storm
Typhoon
5 Apr 2008
19 Apr 2008
3 May 2008
17 May 2008
31 May 2008
14 Jun 2008
28 Jun 2008
Time

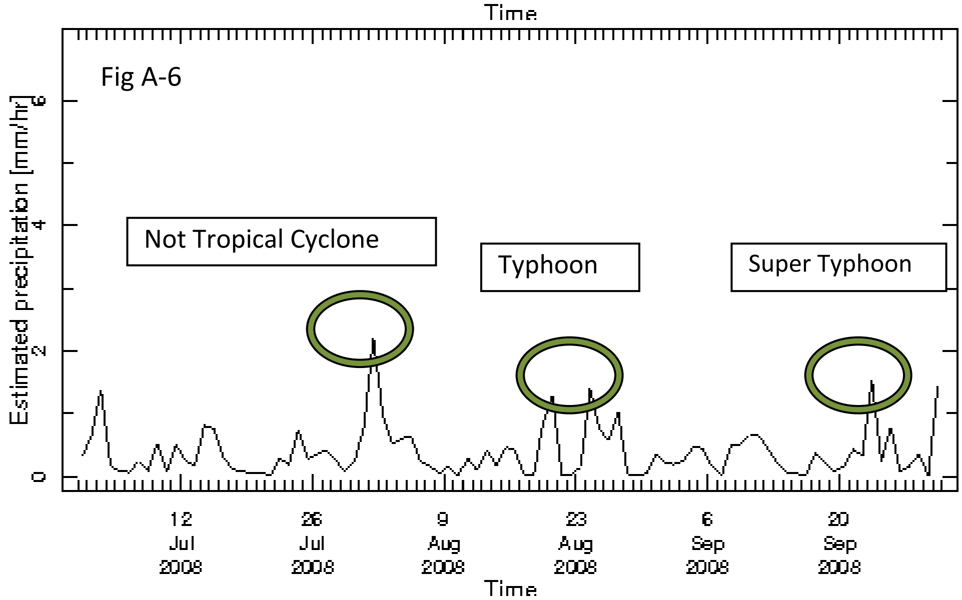
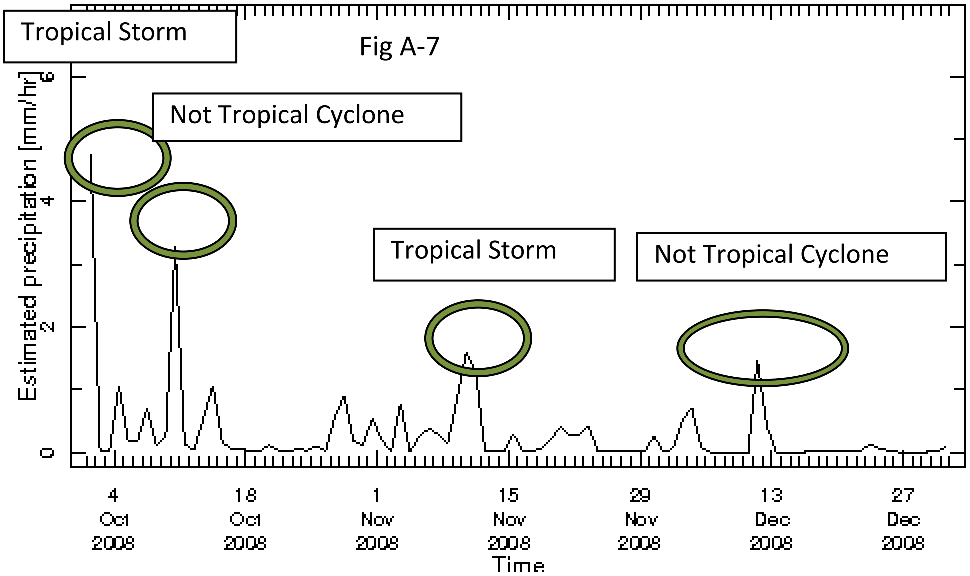


Fig A-6
Estimated precipitation [mm/hr]
0
2
4
6
Not Tropical Cyclone
Typhoon
Super Typhoon
12 Jul 2008
26 Jul 2008
9 Aug 2008
23 Aug 2008
6 Sep 2008
20 Sep 2008
Time


Tropical Storm
Fig A-7
Not Tropical Cyclone
Tropical Storm
Not Tropical Cyclone
Estimated precipitation [mm/hr]
0
2
4
6
4 Oct 2008
18 Oct 2008
1 Nov 2008
15 Nov 2008
29 Nov 2008
13 Dec 2008
27 Dec 2008
Time

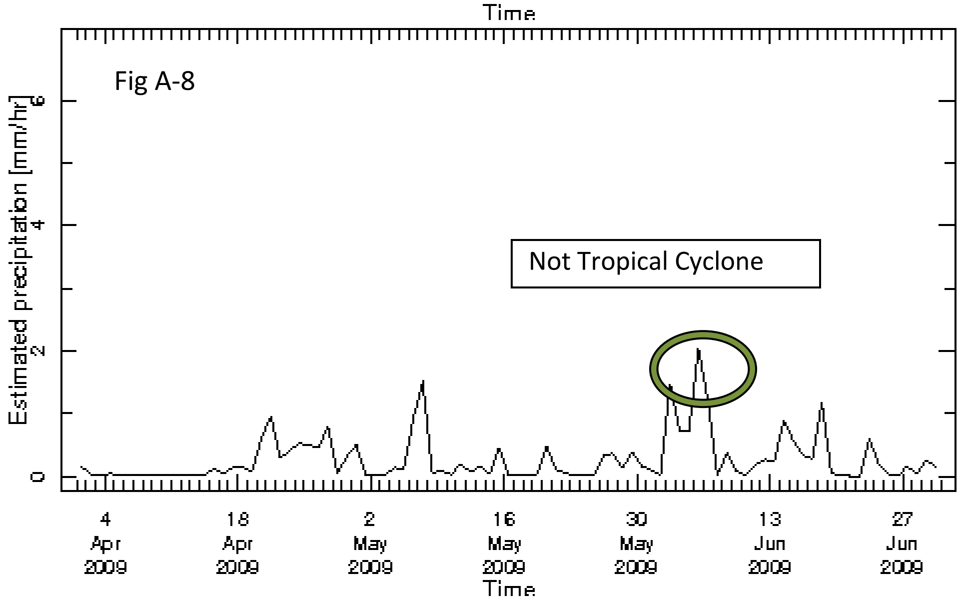


Fig A-8
Not Tropical Cyclone
Estimated precipitation [mm/hr]
0
2
4
6
4 Apr 2009
18 Apr 2009
2 May 2009
16 May 2009
30 May 2009
13 Jun 2009
27 Jun 2009
Time

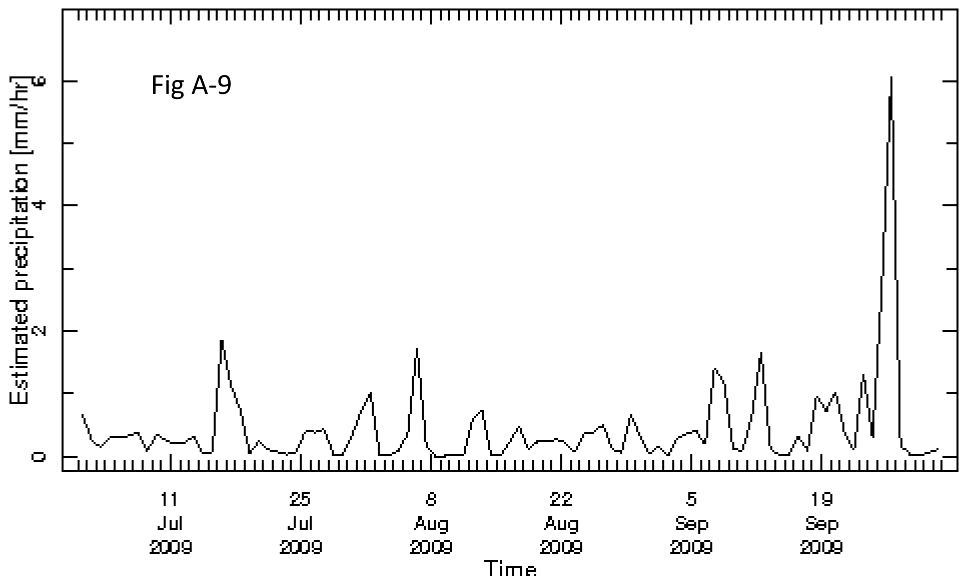


Fig A-9
Estimated precipitation [mm/hr]
0
2
4
6
11 Jul 2009
25 Jul 2009
8 Aug 2009
22 Aug 2009
5 Sep 2009
19 Sep 2009
Time

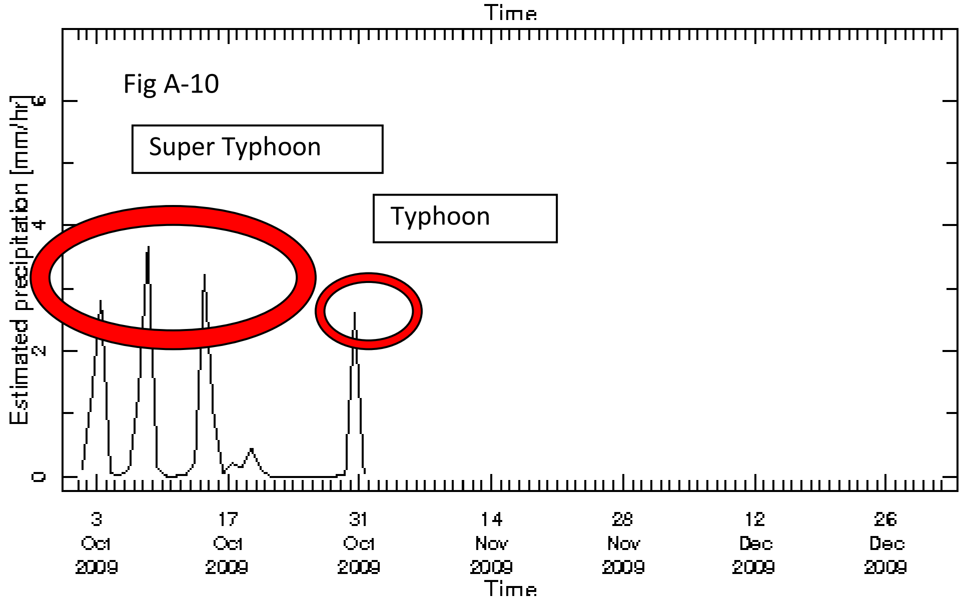


Fig A-10
Super Typhoon
Typhoon
Estimated precipitation [mm/hr]
0
2
4
6
3 Oct 2009
17 Oct 2009
31 Oct 2009
14 Nov 2009
28 Nov 2009
12 Dec 2009
26 Dec 2009
Time

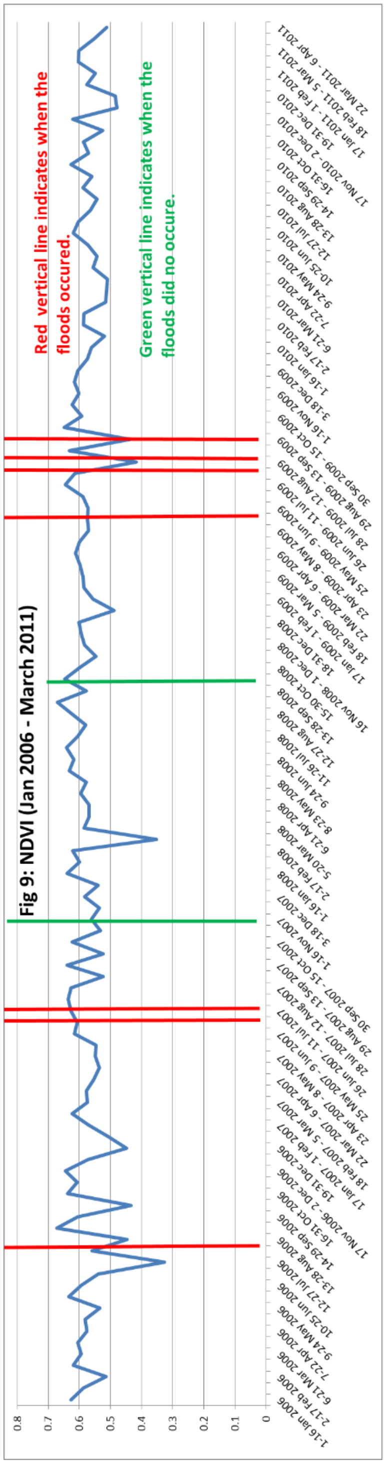



Fig 9: NDVI (Jan 2006 - March 2011)

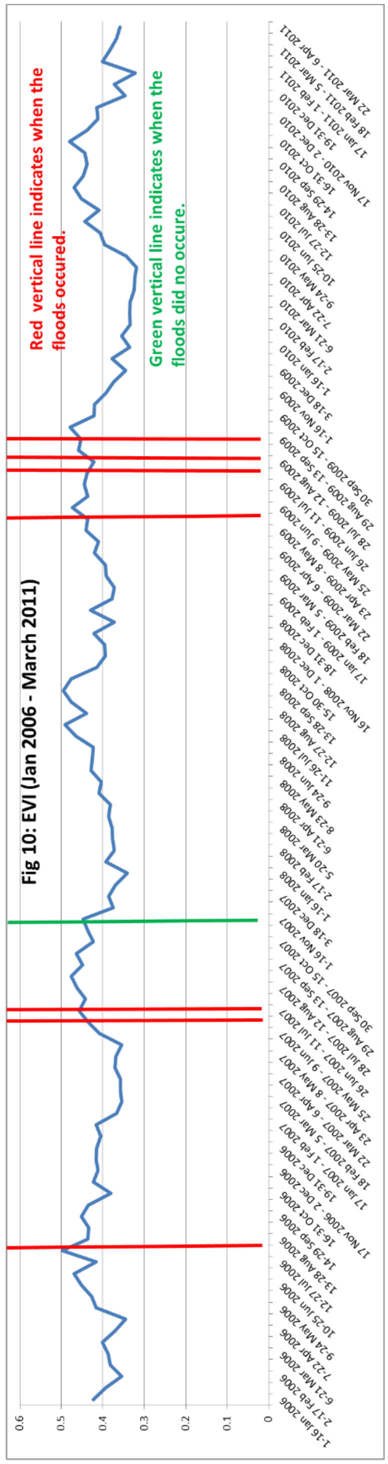



Fig 10: EVI (Jan 2006 - March 2011)

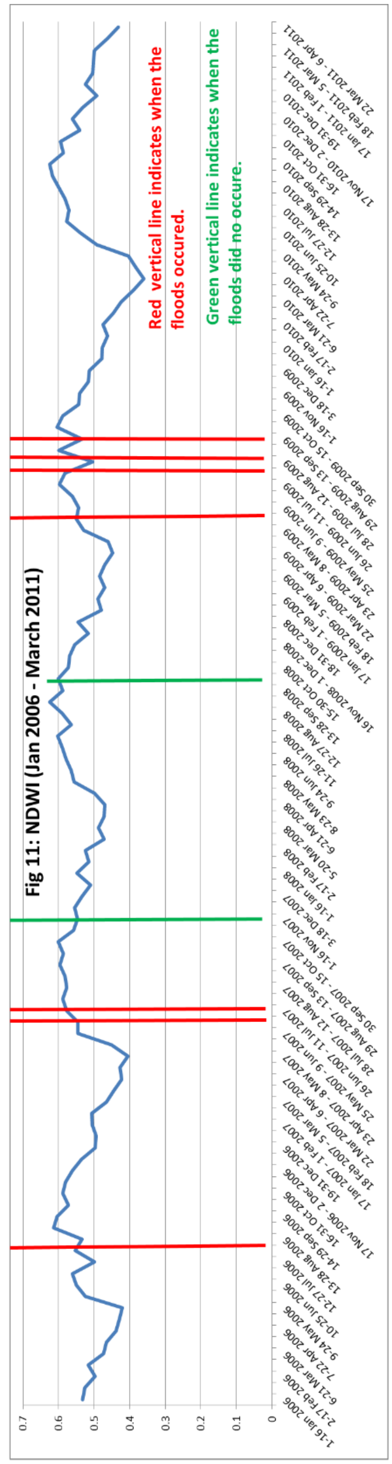



Fig 11: NDWI (Jan 2006 - March 2011)

# Appendix B

Table B-1: Pearson and Spearman correlation coefficients in winter minimum temperature between Mongolia data and Siberia data

| | Southwest | Northwest | East |
|---|---|---|---|
| Pearson correlation coefficients | | | |
| Irkutsk, Siberia | 0.57 | 0.72 | 0.76 |
| Ulan-Ude, Siberia | -0.14 | -0.13 | -0.21 |
| Minusinsk, Siberia | -0.04 | -0.09 | -0.16 |
| Spearman correlation coefficients | | | |
| Irkutsk, Siberia | 0.52 | 0.61 | 0.60 |
| Ulan-Ude, Siberia | -0.14 | -0.19 | -0.22 |
| Minusinsk, Siberia | -0.02 | -0.08 | -0.08 |

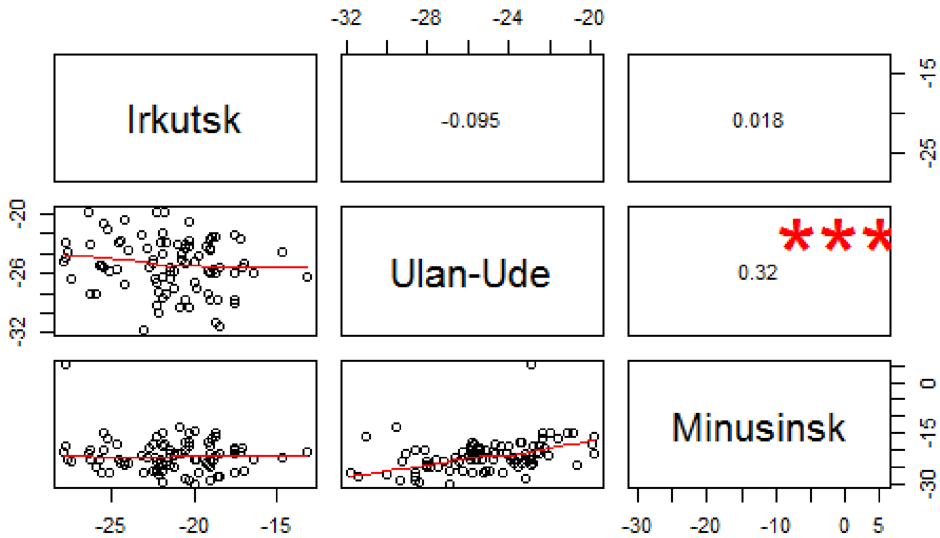



Figure B-1: Scatterplots between winter minimum temperature in three Siberia stations.

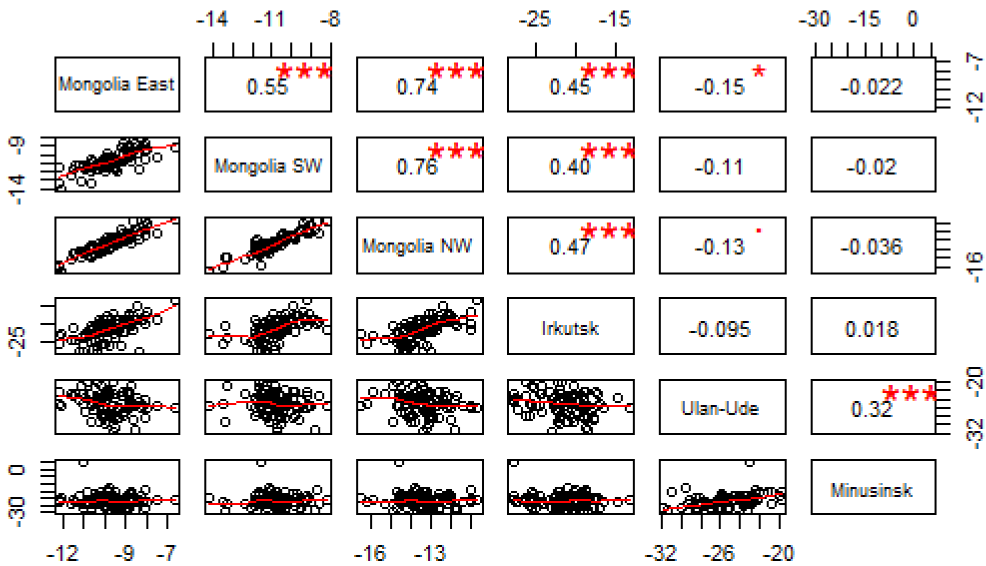



Figure B-2: Scatterplots of winter average temperature in three Siberia and three Mongolia clusters.

# Appendix C

## Appendix C.1: Correlation Analysis Results for Thailand

Table C-1: Highest correlations between different windows of rainfall and areas/durations/damage. "All" means the analysis that uses all the data in Thailand.

| | | Highest correlation |
|---|---|---|
| All | Area | w10 of began date data of reanalysis (0.23) |
| | Durations | w30 of began date data of CPC (0.28) |
| Top 20 events in terms of areas | Area | w30 of mid date data of CPC (0.33) |
| | Durations | w30 of mid date data of reanalysis (0.15) |
| | Damage | W1 –w2 of mid date data of reanalysis (0.36) |
| Top 20 events in terms of durations | Area | w30 of began date data of reanalysis (0.36) |
| | Durations | w30 of began date data of reanalysis (0.26) |
| | Damage | W1 of mid-date data of reanalysis (0.22) |
| Top 20 events in terms of damages | Area | W2 of began date of CPC , w4 of began date of reanalysis . (0.29) |
| | Durations | W5 of began-date data of CPC (0.31) |
| | Damage | W5 of began-date data of CPC (0.08) |

## Appendix C.2: Bangladesh's Flood Data

Flood data are obtained first from Dartmouth Flood Observatory (DFO), whose data are available from 1985 until the present. The total number of recorded floods is 87. Among them, 15 events have economic loss data. The median flooded area is 24,000 km$^2$. The median flood duration is 8 days while the maximum duration is 122 days. In addition to DFO and BWBD, seasonal surface water is also calculated (Lall et al., 2017). Three datasets are plotted in Figure 7-15. There are still big discrepancies among these three data sets. Looking at the correlation coefficients based on rankings (Kendall τ), DFO and BWBD have a higher coefficient (Table C-2).

Table C-2: Correlation Coefficients among the three data for flood affected areas (Kendall's tau)

| | Seasonal Surface Water | DFO |
|---|---|---|
| BWBD | 0.226 | 0.336 |
| Seasonal Surface Water | - | 0.079 |

## Appendix C.3: Analysis of Rainfall, Streamflow, and Water Level Data in Bangladesh

Table 7-8 shows that 1-day and 2-day windows have the highest correlation coefficients between flooded areas and different rainfall windows. However, they were not so strongly associated with catastrophic flood events. For example, Figure C-1 shows the time series of the highest time windows (the 1-day and 2-day windows) and flood affected areas. The largest flood event in 1998 is not associated with rainfall amounts. In addition, Figure 7-10 shows that large rainfall events are not associated with flood occurrences in the 1-day and 2-day windows while they are associated with flood occurrences in longer windows such as the 30-day window. One of possible reasons of this is that river inflow from India might be affecting the flood situations.

Thus, next we examine the following two relationships:

- Streamflow data and rainfall amounts.
- Streamflow data and flood affected areas.

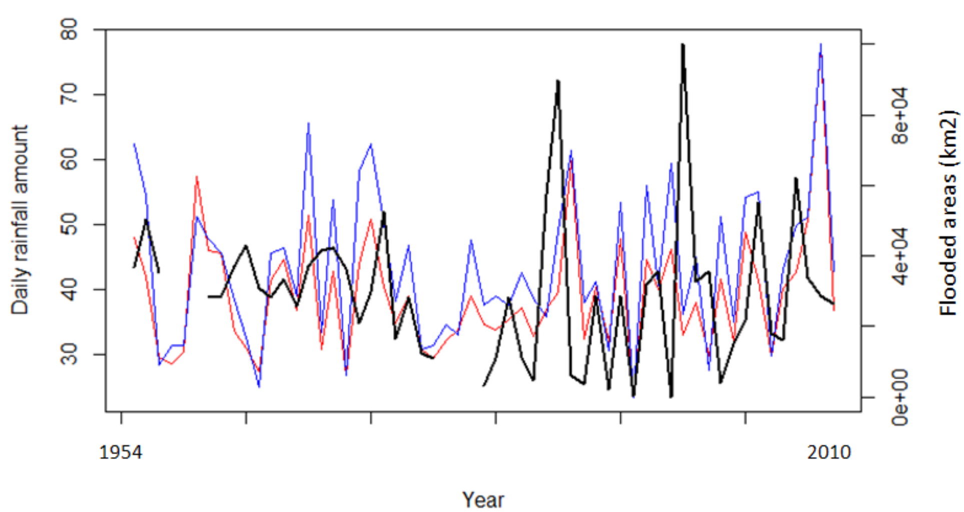



Figure C-1: Time Series of the 1-day and 2-day windows and flood affected areas. The blue line is daily rainfall amounts of the 1-day window, the red line is daily rainfall amounts of the 2-day window, and the black line is flood affected areas (km2)

## Appendix C.4: Correlation Analysis between Rainfall, Streamflow and Water levels, and Flooded Areas in Bangladesh

We conduct the below analysis for 3 parts:

1) Relationships among annual max of different rainfall windows, streamflow, and flood areas (Figure C-2 to Figure C-4).

2) Relationships among seasonal total rainfalls, max wet spell, streamflow and flood areas (Figure C-5 to Figure C-7). Seasons are Oct - Feb-winter, March - May: summer, June-Sept: rain season. The sites are monthly streamflow (1956 - 2000) in Bahadurabad in Bangladesh, daily streamflow (1994, 1995, 1997 – 2011) in Beki River in India, and daily discharge (1992 – 2009) in Brahmaputra site in Pandu, Guwahati, India.

3) Relationships among seasonal total rainfalls, max wet spell, water levels and flood areas (Figure C-8 to Figure C-10). Sites are Daily water level at Bahadurabad, daily water level at Rajshashi Ganges, daily water level at Bhairab and Bazar Meghna.

The below data in Table C-3 are used for this analysis.

Table C-3: List of streamflow and water level data

| Site | Type |
|---|---|
| **Streamflow** | |
| Brahmaputra River, monitored in Bahadurabad in Bangladesh | • Daily streamflow (1985 – 1992)[1]<br>• Monthly streamflow (1956 - 2000) no missing values[1]<br><br>• Daily (1998 – Nov20, 2006)[2]<br>• Monthly (1956 – 1995, with NA) [3]<br>• Monthly (1969 – March 92, with NA)[4]<br>• Monthly (1998 – Nov 2011 with NA)[2] |
| Beki River in India | Daily streamflow (1994, 1995, 1997 – 2011) [1]<br>(But about 40% are missing values: Jan 96 – July 97, Jan 2001 – Dec 2002, May 2003 – Sept 2003, Jan 2005 – Dec 2005, May 2008 – Sept 2008, Jan 2010 – Dec 2010, July 2011 – Dec 2011) |
| Brahmaputra River, monitored in Pandu, Guwahati, India | • Daily discharge (1992 – April 1998) missing values are 4%.[1]<br>• Once a week to get data for discharge (May 1998 – Dec 2009)[1]<br>• Level discharge (2010 – 2013)[1] |
| **Water level** | |
| Daily water level at Bahadurabad (m)[2] | Daily water level (April 1949 – Oct 2009) missing values are 4%. |
| Daily water level at Rajshashi (m)[2] | Daily water level (April 1922 – Dec 2006), missing values are 25% (mostly April 1938 – Dec 1957). |
| Daily water level at Bhairab Bazar (m)[2] | Daily water level (April 1959 – July 2006), missing values are 17%, |

1 is data given by Prof. Soojun Kim; 2 is data given by Prof. EthanYang; 3 is data from Yu et al through Yang; 4 is data from GRDC 2013 through Yang)

As the results attached in Table C-4 - Table C-7, the correlation coefficients, Kendall's τ, are mostly negative or close to zero. Thus, in the section of Appendix C.5: Analysis of Standardized Anomaly in the Streamflow and Water Levels in Bangladesh, the standardized anomaly is analyzed.

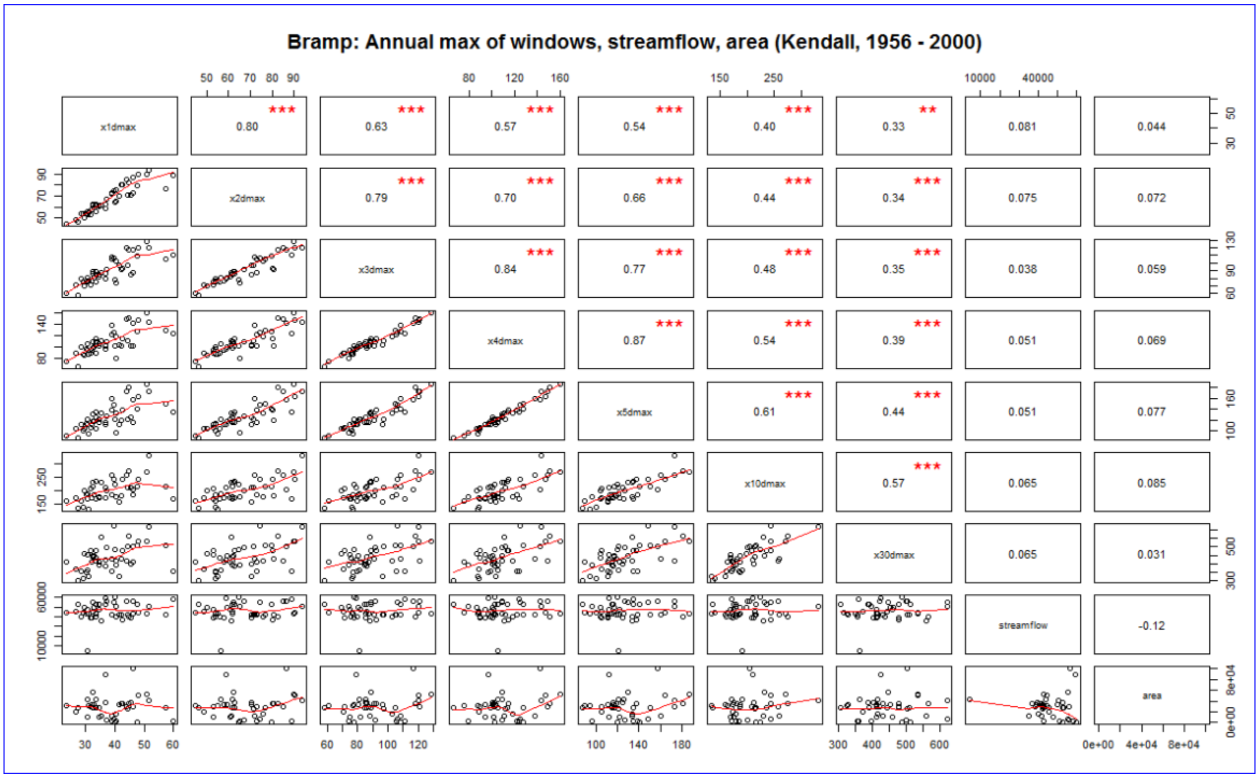



Figure C-2: Rank correlation by the Kendall method among the annual max of windows, streamflow, and area, using data from the Brahmaputra River in Bahadurabad in Bangladesh (1956 – 2000)

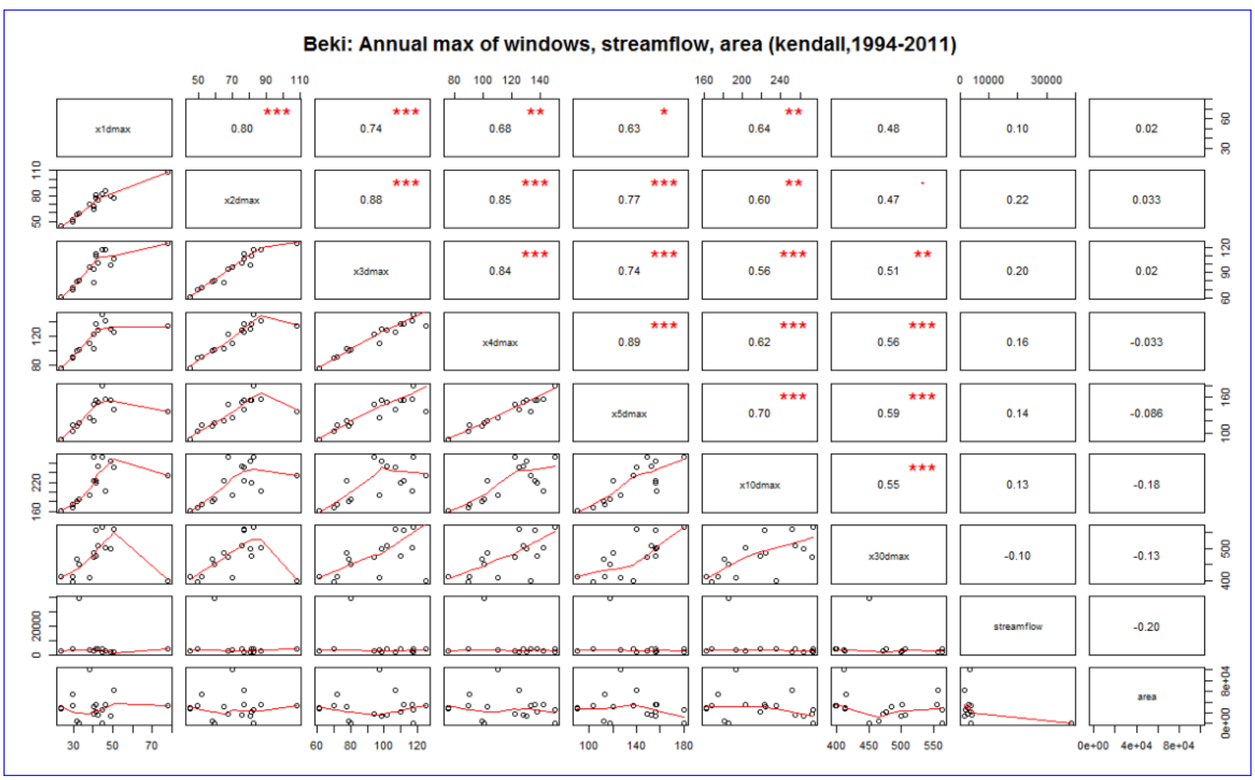


Figure C-3: Rank correlation by the Kendall method among annual max of windows, streamflow, and areas, using data from the Beki River in India (1994 – 2011)

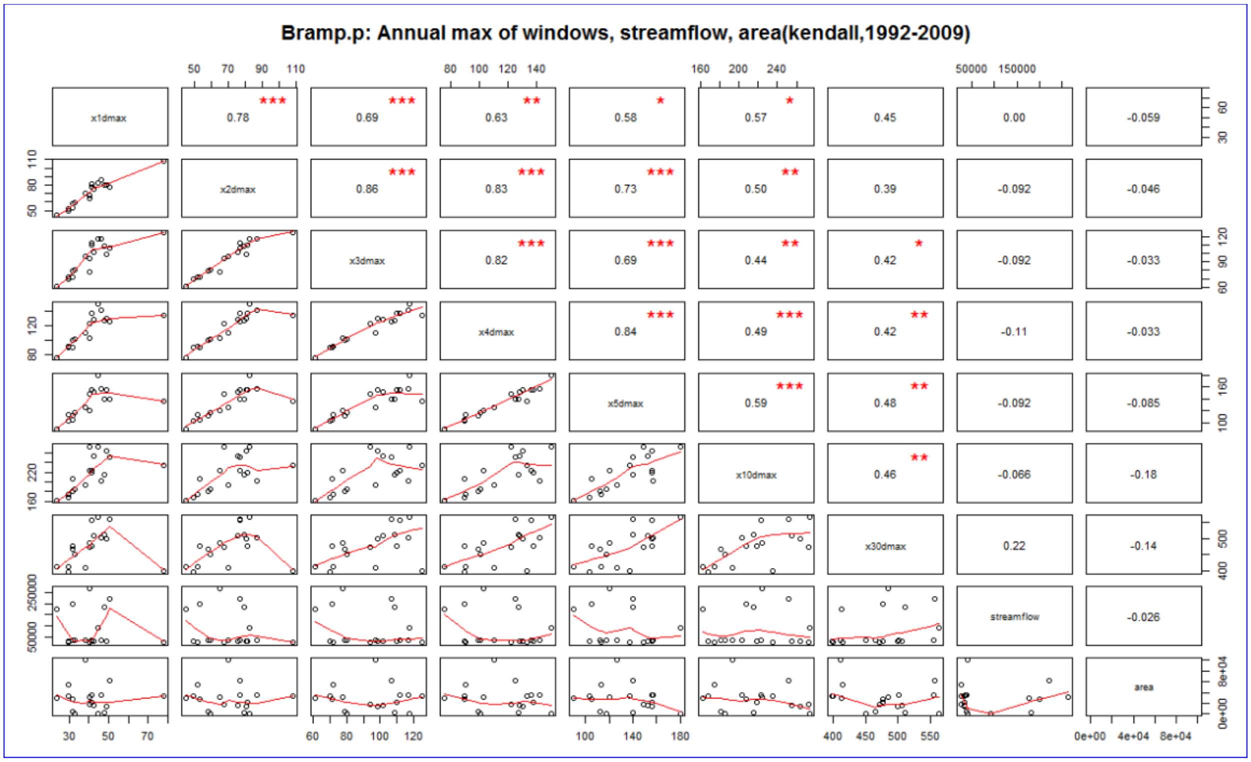



Figure C-4: Rank correlation by the Kendall method among annual max of windows, streamflow, and areas, using data from the Brahmaputra River in Pandu, Guwahati, India (1992 – 2009)

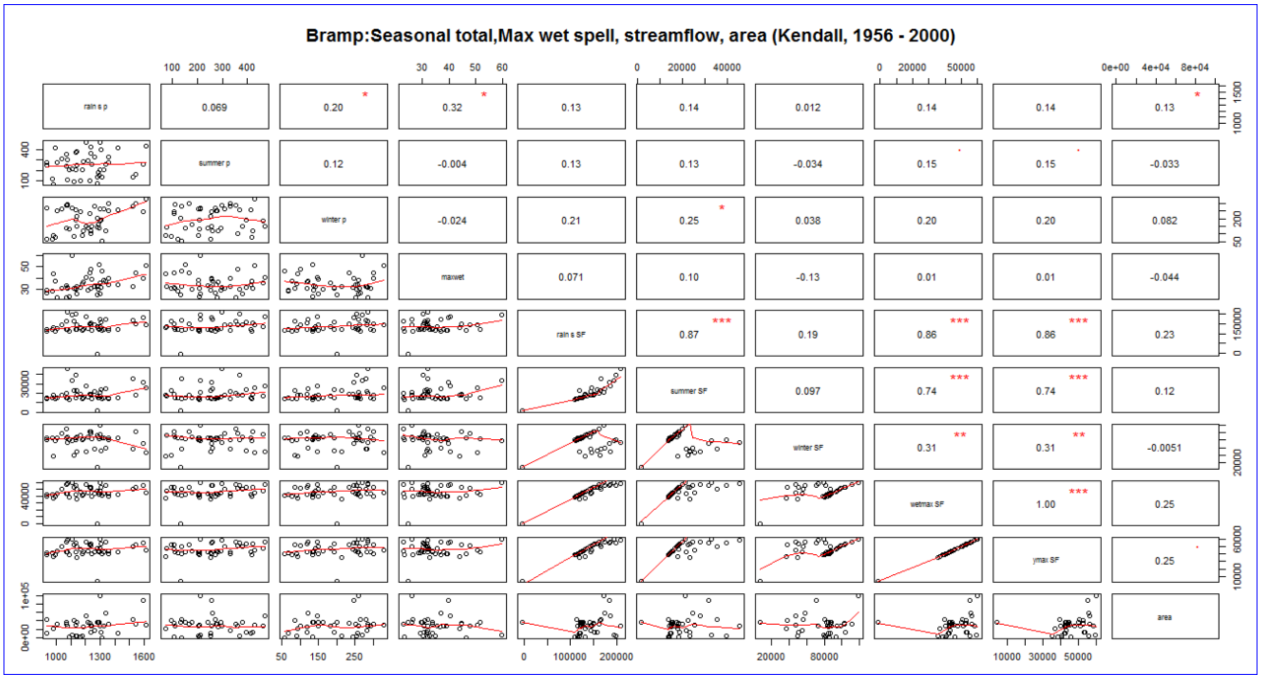



Figure C-5: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, and areas, using the data from the Brahmaputra River in Bahadurabad in Bangladesh (1956 – 2000).

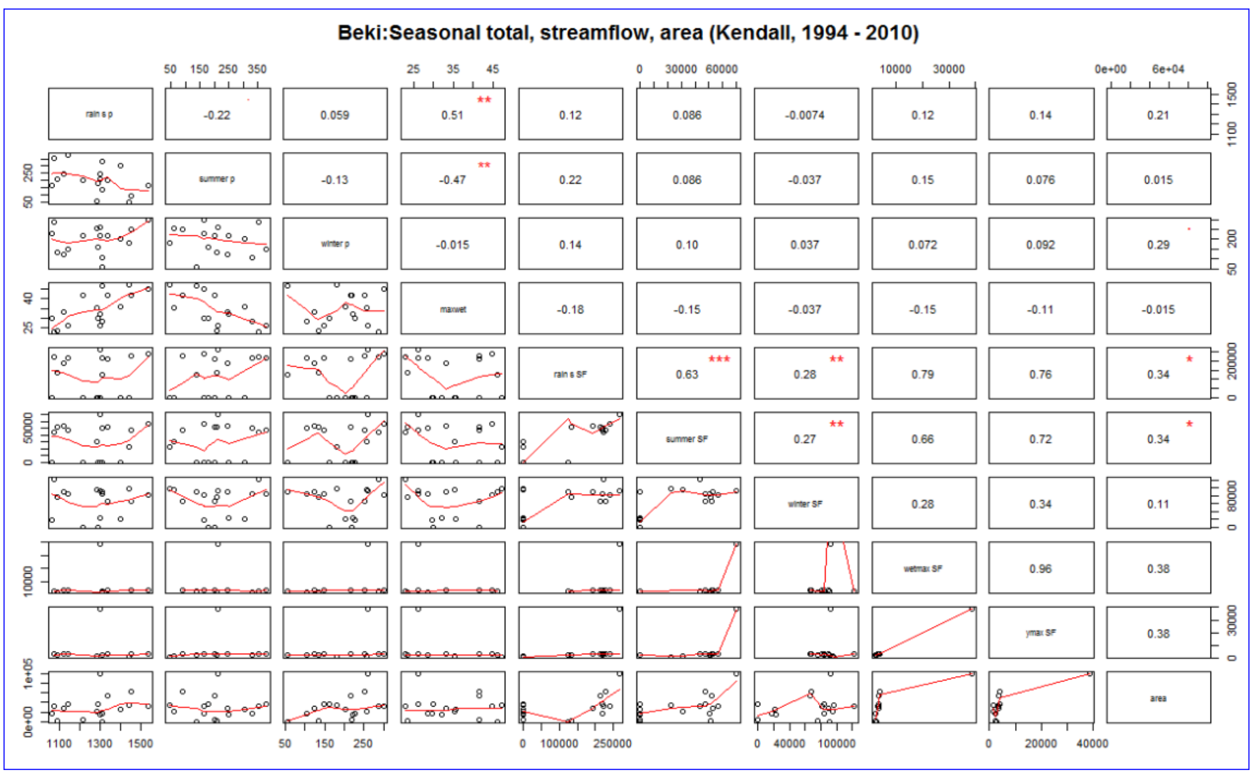



Figure C-6: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, and areas, using data from the Beki River in India (1994 – 2010).

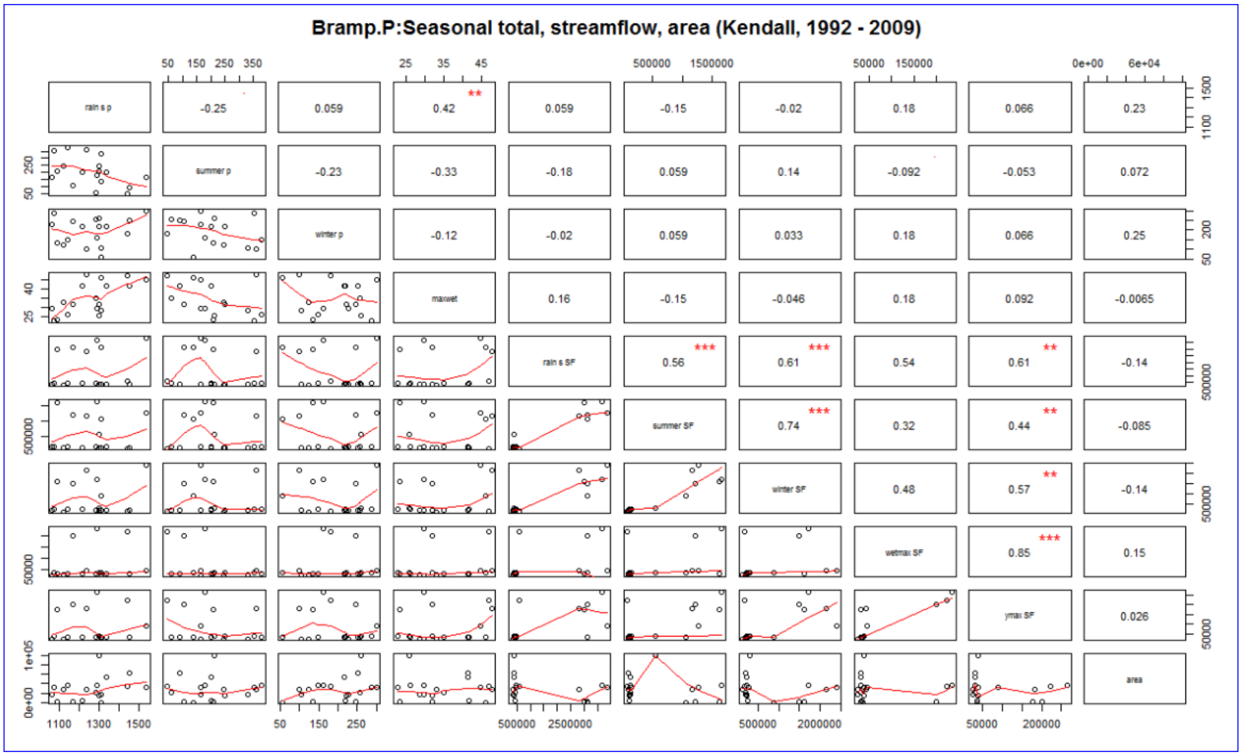



Figure C-7: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, areas for the Brahmaputra River in Pandu, Guwahati, India (1992 – 2009).

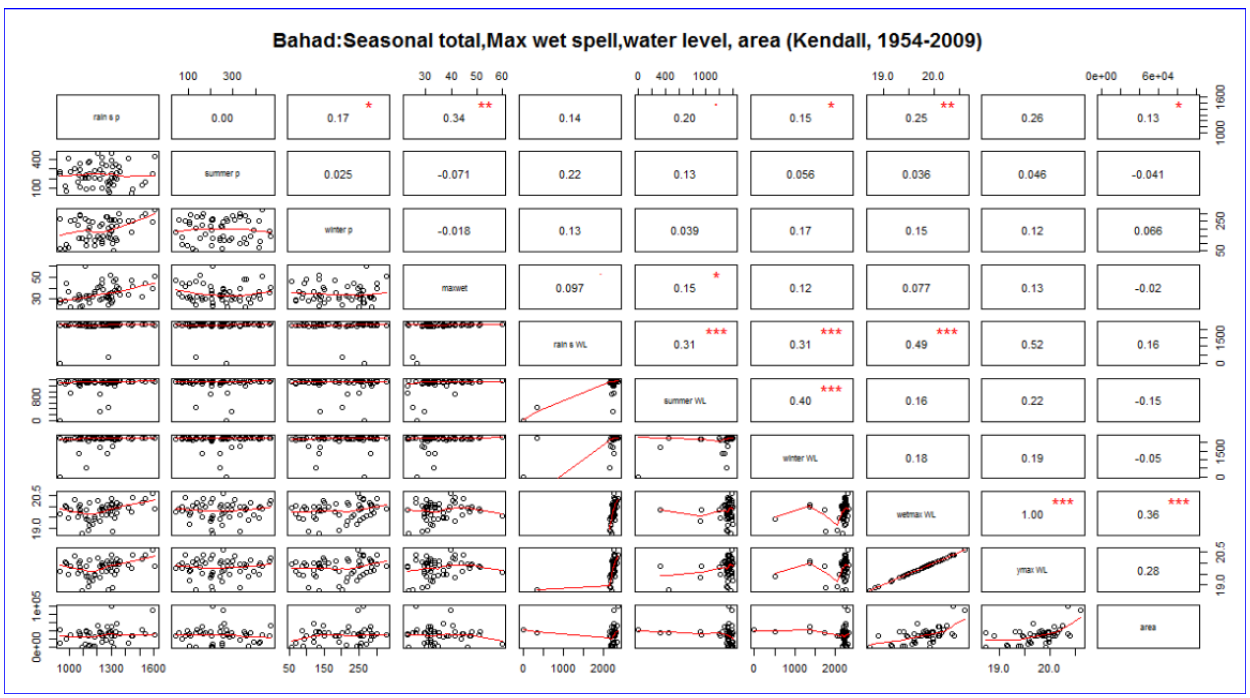



Figure C-8: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, and areas from the Brahmaputra River in Bahadurabad in Bangladesh (1954 – 2009).

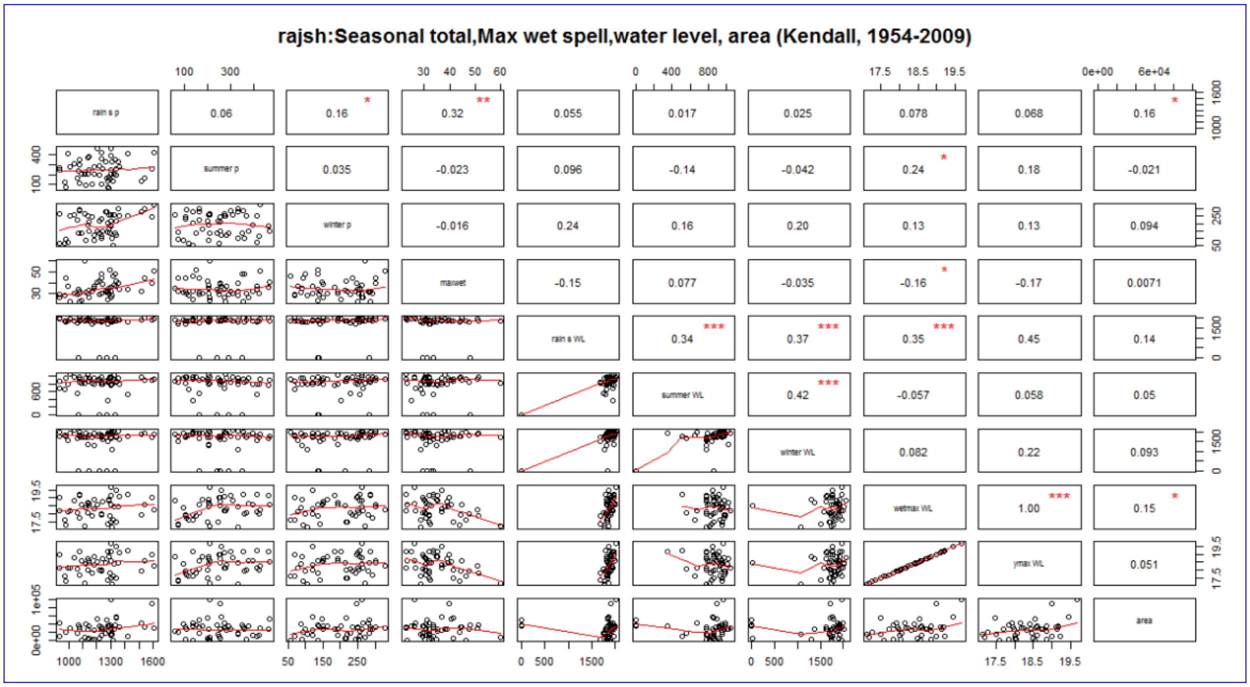



Figure C-9: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, areas at Rajshashi along the Ganges River (1954 – 2009).

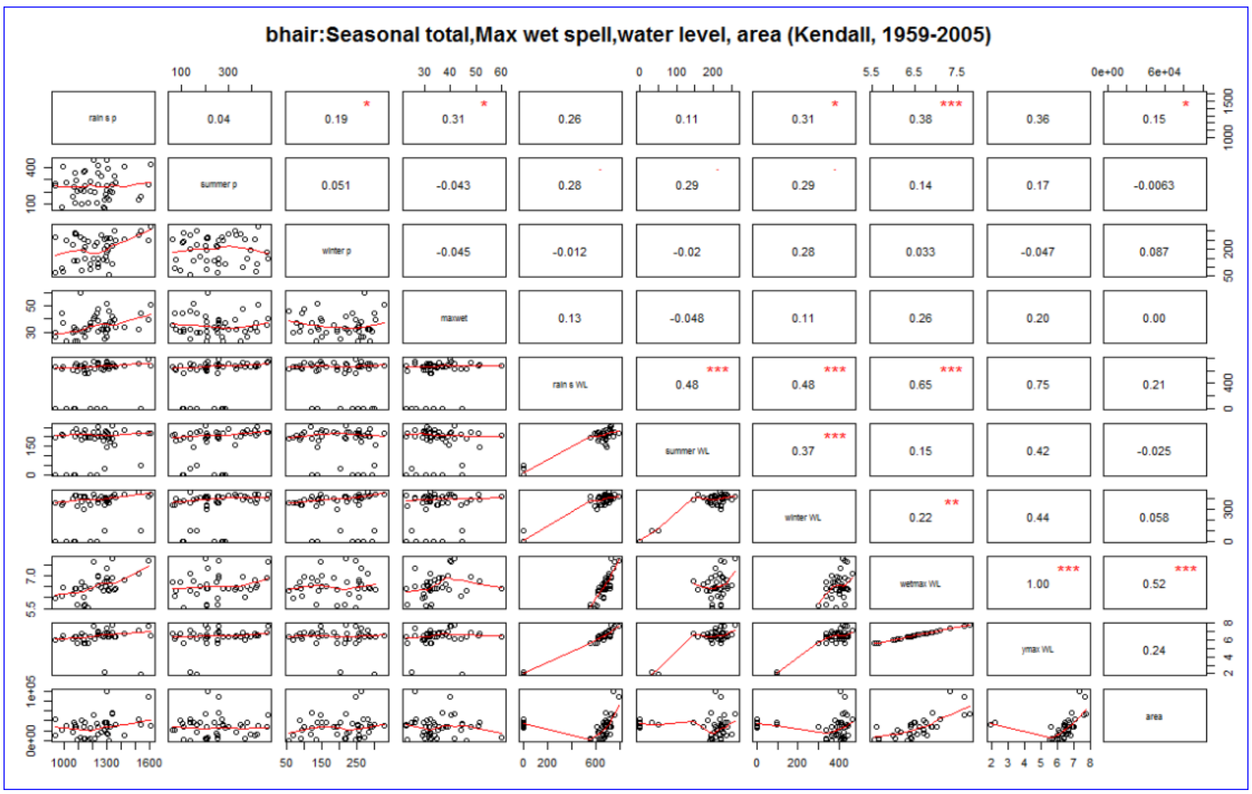



Figure C-10: Rank correlation by the Kendall method among seasonal total, max wet spell, streamflow, and areas at Bhairab Bazar along the Meghana River (1959 – 2005).

## Appendix C.5: Analysis of Standardized Anomaly in the Streamflow and Water Levels in Bangladesh

Table C-4: Streamflow at Bahadurabad in Bangladesh (1956-2000) for the Brahmaputra River for the top 10 events in terms of flood affected area.

| Year | Total rainfall during a rainy season | Total summer rainfall | Total winter rainfall | Max precipitation during a rainy season | Total streamflow during a rainy season | Total streamflow during summer | Total streamflow during winter | Flooded areas (km2) |
|---|---|---|---|---|---|---|---|---|
| 1998 | 0.81 | -0.28 | 0.68 | -0.64 | 1.02 | 0.23 | 1.87 | 100250 |
| 1988 | 2.22 | 0.13 | 0.50 | 0.88 | 1.39 | 1.58 | -0.39 | 89970 |
| 1987 | 1.00 | 0.15 | -1.05 | 0.58 | 1.07 | 0.68 | -0.96 | 57300 |
| 1974 | 0.37 | 2.02 | -0.72 | 0.97 | 1.42 | 1.12 | -1.43 | 52600 |
| 1963 | -0.94 | 0.27 | 0.75 | -0.59 | -0.72 | -0.69 | 0.06 | 43100 |
| 1970 | 1.88 | -0.93 | 0.92 | 0.03 | 0.85 | 2.05 | -1.05 | 42400 |
| 1969 | -0.04 | -1.31 | -1.48 | -0.1 | 0.81 | 0.40 | -1.88 | 41400 |
| 1962 | -0.31 | -0.01 | -0.86 | 0.21 | -0.44 | -0.54 | 0.28 | 37200 |
| 1968 | 0.79 | -0.81 | -0.87 | 2.20 | -0.49 | -0.57 | 0.18 | 37200 |
| 1971 | 0.73 | -0.97 | -0.05 | -0.77 | -4.22 | -2.30 | -3.34 | 36300 |

Table C-5: Water levels at Bahadurabad (1954-2009) for the top 10 events in terms of flood affected area.

| Year | Total rainfall during a rainy season | Total summer rainfall | Total winter rainfall | Max precipitation during a rainy season | Total water level during a rainy season | Total water level during summer | Total water level during winter | Flooded areas (km2) |
|---|---|---|---|---|---|---|---|---|
| 1998 | 0.81 | -0.28 | 0.68 | -0.64 | 0.56 | 0.33 | 0.33 | 100250 |
| 1988 | 2.22 | 0.13 | 0.5 | 0.88 | 0.22 | 0.52 | 0.58 | 89970 |
| 2007 | 1.56 | -1.38 | 0.57 | 1.09 | 0.19 | 0.22 | 0.28 | 62300 |
| 1987 | 1 | 0.15 | -1.05 | 0.58 | 0.18 | 0.3 | 0.42 | 57300 |
| 2004 | 0.99 | -0.38 | 0.15 | 1.08 | 0.11 | 0.5 | 0.39 | 55000 |
| 1974 | 0.37 | 2.02 | -0.72 | 0.97 | 0.46 | 0.55 | 0.43 | 52600 |
| 1955 | 0.69 | -0.72 | 0.95 | -0.08 | 0.16 | -0.04 | -2.73 | 50500 |
| 1963 | -0.94 | 0.27 | 0.75 | -0.59 | NA | NA | NA | 43100 |
| 1970 | 1.88 | -0.93 | 0.92 | 0.03 | 0.28 | 0.51 | 0.29 | 42400 |
| 1969 | -0.04 | -1.31 | -1.48 | -0.1 | 0.2 | 0.27 | 0.1 | 41400 |

Table C-6: Water levels at Rajshashi along the Ganges River (1960 - 2006) for the top 10 events in terms of flood affected area.

| Year | Total rainfall during a rainy season | Total summer rainfall | Total winter rainfall | Max precipitation during a rainy season | Total water level during a | Total water level during summer | Total water level during winter | Flooded areas (km2) |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | rainy season | | | |
| 1998 | 0.81 | -0.28 | 0.68 | -0.64 | 1.77 | 0.83 | 0.75 | 100250 |
| 1988 | 2.22 | 0.13 | 0.5 | 0.88 | 0.29 | 0.29 | -0.08 | 89970 |
| 1987 | 1 | 0.15 | -1.05 | 0.58 | -0.17 | -0.07 | 0.13 | 57300 |
| 2004 | 0.99 | -0.38 | 0.15 | 1.08 | -0.57 | 0.04 | -0.04 | 55000 |
| 1974 | 0.37 | 2.02 | -0.72 | 0.97 | -0.34 | 0.27 | 0.19 | 52600 |
| 1963 | -0.94 | 0.27 | 0.75 | -0.59 | 0.9 | -1.36 | 0.84 | 43100 |
| 1970 | 1.88 | -0.93 | 0.92 | 0.03 | 0.4 | 0.96 | 0.49 | 42400 |
| 1969 | -0.04 | -1.31 | -1.48 | -0.1 | 0.18 | 0.75 | 0.58 | 41400 |
| 1962 | -0.31 | -0.01 | -0.86 | 0.21 | NA | NA | NA | 37200 |
| 1968 | 0.79 | -0.81 | -0.87 | 2.2 | -0.07 | 0.97 | 0.61 | 37200 |

Table C-7: Water levels at Bhairab Bazar along the Meghana River for the top 10 events in terms of flood affected area.

| Year | Total rainfall during a rainy season | Total summer rainfall | Total winter rainfall | Max precipitation during a rainy season | Total water level during a rainy season | Total water level during summer | Total water level during winter | Flooded areas (km2) |
|---|---|---|---|---|---|---|---|---|
| 1998 | 0.81 | -0.28 | 0.68 | -0.64 | 1.1 | 0.05 | 0.32 | 100250 |
| 1988 | 2.22 | 0.13 | 0.5 | 0.88 | 1.63 | 0.45 | 0.56 | 89970 |
| 1987 | 1 | 0.15 | -1.05 | 0.58 | 0.22 | -0.21 | 0.57 | 57300 |
| 2004 | 0.99 | -0.38 | 0.15 | 1.08 | 0.78 | 1.36 | 0.47 | 55000 |
| 1974 | 0.37 | 2.02 | -0.72 | 0.97 | 1.16 | 0.61 | 0.75 | 52600 |
| 1963 | -0.94 | 0.27 | 0.75 | -0.59 | NA | NA | NA | 43100 |
| 1970 | 1.88 | -0.93 | 0.92 | 0.03 | 0.58 | 0.37 | 1.08 | 42400 |
| 1969 | -0.04 | -1.31 | -1.48 | -0.1 | 0.2 | -0.43 | -0.09 | 41400 |
| 1962 | -0.31 | -0.01 | -0.86 | 0.21 | NA | NA | NA | 37200 |
| 1968 | 0.79 | -0.81 | -0.87 | 2.2 | 0.4 | -1.34 | 0.15 | 37200 |

## Appendix C.6: Other Way of Selecting Predictors for Trigger Levels

One may use Local regression and the Least Absolute Shrinkage and Selection Operator (LASSO) as other ways of selecting significant predictors so as to identify trigger levels. Here we show the results for the purpose of the demonstration.

### Conducting local regressions of BWBD data

Local regression is used to fit a smooth curve among the predictors. The advantage of the local regression is that it can relax the linearity assumption of conventional regression methods. Based on the minimum generalized cross-validation (GCV) scores, the selected predictor was the maximum water level in a rainy season in Bhairab Bazar (Table C-8).

Table C-8: Results of local regressions with GCVs for BWBD data.

| Predictors | GCV |
|---|---|
| Rain_Precip | 4.804642e+08 |
| RainWL | 2.922312e+08 |
| SummerWL | 7.013183e+08 |
| WinterWL | 6.248909e+08 |
| Rain_Precip, RainWL | 4.586061e+08 |
| Rain_Precip, SummerWL | 6.692367e+08 |
| Rain_Precip, WinterWL | 9.628752e+08 |
| RainWL, SummerWL | 3.676626e+08 |
| SummerWL, WinterWL | 1.048159e+09 |
| Rain_Precip, RainWL, SummerWL | 8.903630e+08 |
| Rain_Precip, RainWL, winterWL | 2.940885e+09 |
| Rain_Precip, SummerWL, WinterWL | 1.870981e+09 |
| RainWL, SummerWL, WinterWL | 1.091053e+09 |
| All | 1.678401e+10 |

## Logistic regression with LASSO

Another way to select predictors is to use Lasso (Least Absolute Shrinkage and Selection Operator). After recording an event if flood events exceed a threshold of the 80 and 90 percentiles, logistic regression is conducted with Lasso (Least Absolute Shrinkage and Selection Operator). Lasso is a shrinkage method by adding a penalty term.

For the 80$^{th}$ percentile of the BWBD data (Annual data from 1960 – 2006), 8 years are recorded as flooding years: 1963, 1969, 1970, 1974, 1987, 1988, 1998, and 2004. For the 90$^{th}$ percentile of the BWBD data, four years are recorded as flooding years: 1987, 1988, 1998, and 2004. Figure C-11 and Figure C-12 show the relationship between L1 norm and coefficients of the logistic regression for the case where the top 10 percentile events are recorded as floods and the case of the top 20 percentile, respectively.

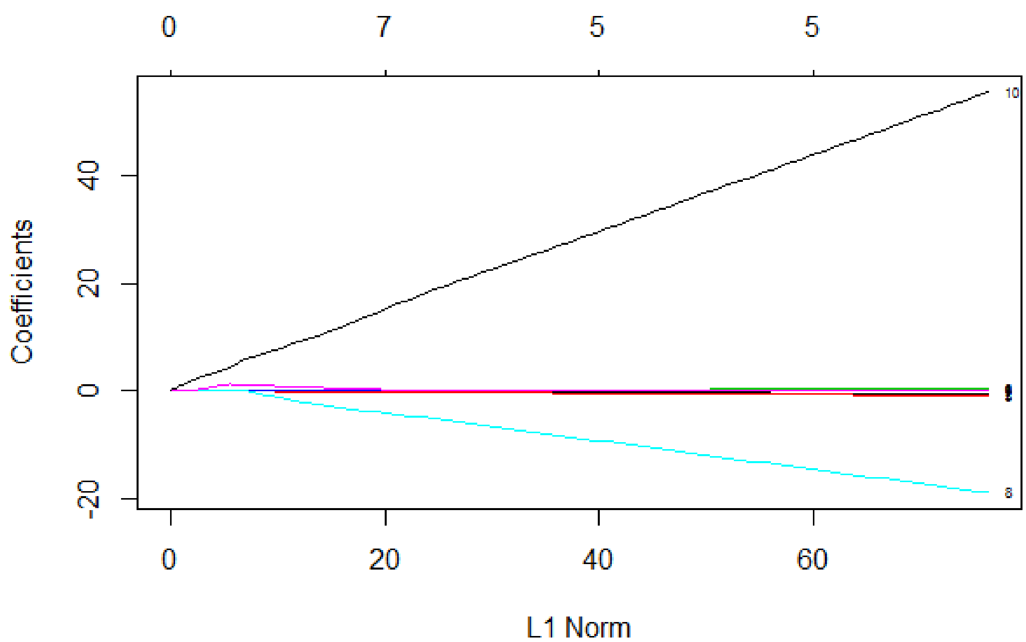



Figure C-11: The path of its coefficient of the logistic regression against the L1-norm of the whole coefficient vector as λ varies when the upper 10th percentile of BWBD's data was recorded as floods. The axis above is the number of nonzero coefficients at the current λ. Labels 1: The maximum precipitation with the 1 day window; 2: The maximum precipitation with the 2 days window; 3: The maximum precipitation with the 3 days window; 4: The maximum precipitation with the 4 days window; 5: The maximum precipitation with the 5 days window; 6: The maximum precipitation with the 10 days window; 7: The maximum precipitation with the 30 days window; 8: The maximum water level in Bahadurabad (Brahmaputra river); 9: The maximum water level in Rajshashi (Ganges river); 10: The maximum water level in Bhairab Bazar (Meghna River)

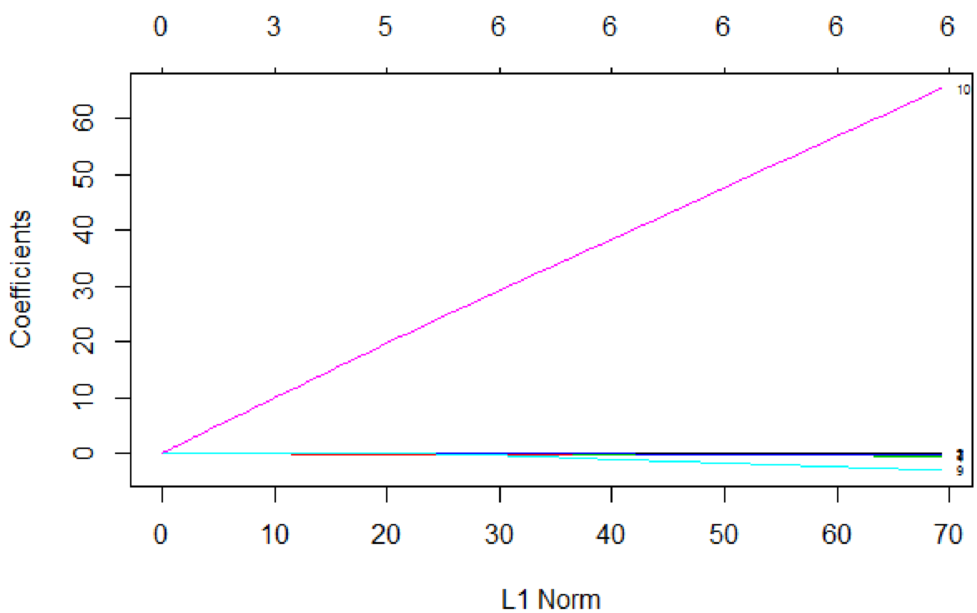



Figure C-12: The path of its coefficient of the logistic regression against the L1-norm of the whole coefficient vector as λ varies when the upper 20th percentile of BWBD's data was recorded as floods. The axis above is the number of nonzero coefficients at the current λ. Labels 1: The maximum precipitation with the 1 day window; 2: The maximum precipitation with the 2 days window; 3: The maximum precipitation with the 3 days window; 4: The maximum precipitation with the 4 days window; 5: The maximum precipitation with the 5 days window; 6: The maximum precipitation with the 10 days window; 7: The maximum precipitation with the 30 days window; 8: The maximum water level in Bahadurabad (Brahmaputra river); 9: The maximum water level in Rajshashi (Ganges river); 10: The maximum water level in Bhairab Bazar (Meghna River)

Because BWBD's data that uses top 10 percentile as a threshold has missing values, the data for the government data is imputed by Gibbs sampling using predictive mean matching method (Buuren & Groothuis-Oudshoorn, 2011). To select variables, the coefficients of cross validation (with 10-fold) based on the minimum λ are examined as above. Table C-9, as other tables in the below, shows validate variables based on cross-validation. For the data that records top 10 percentile as floods, the selected model uses the maximum water level in Rajshashi (Ganges River) and Bhairab Bazar (Meghna River). The selected model for the data of the top 20 percentile as a threshold uses the maximum rainfall amounts for 3-day and 30days window, and the maximum water level in Bhairab Bazar (Meghna).

The time series of the observations (red line) and predicted values (black line) by the best model for the 90$^{th}$ and 80$^{th}$ percentile data, in Figure C-13 and Figure C-14 respectively. In Figure C-13, the model accurately predicts occurrence of flooding with more than 50% probability for 1987, 1988, and in 1998. For the 2004 floods, the model predicts it as a 41% of probability. Yet, 1974 was predicted as a flood year, but in fact the actual flood did not occur. In Figure C-14, the model accurately predicts floods occurrence with more than 50% of probability in 1974, 1988, 1998, and 2004. It falsely predicted floods in 1962 and 1971 even though both years did not actually record floods. Furthermore, 1963, 1969, 1970, 1987 cannot be predicted by the model.

Table C-9: Variable selection based on 10-fold cross-validation for the 90$^{th}$ and 80$^{th}$ percentile in BWBD's data recorded as floods.

| Variables | Coefficients for 90$^{th}$ percentile data | Coefficients for 80$^{th}$ percentile data |
|---|---|---|
| Intercept | -35.74 | -42.42 |
| Maximum rainfall amounts in 1-day window | - | - |
| Maximum rainfall amounts in 2-day window | - | - |
| Maximum rainfall amounts in 3-day window | - | -0.03 |
| Maximum rainfall amounts in 4-day window | - | - |
| Maximum rainfall amounts in 5-day window | - | - |
| Maximum rainfall amounts in 10-day window | - | - |
| Maximum rainfall amounts in 30-day window | - | -0.01 |
| Max Bahadurabad Water Level | - | - |
| Max Water Level in Rajshashi | 0.65 | - |
| Max water level in Bhairab Bazar | 3.14 | 7.03 |

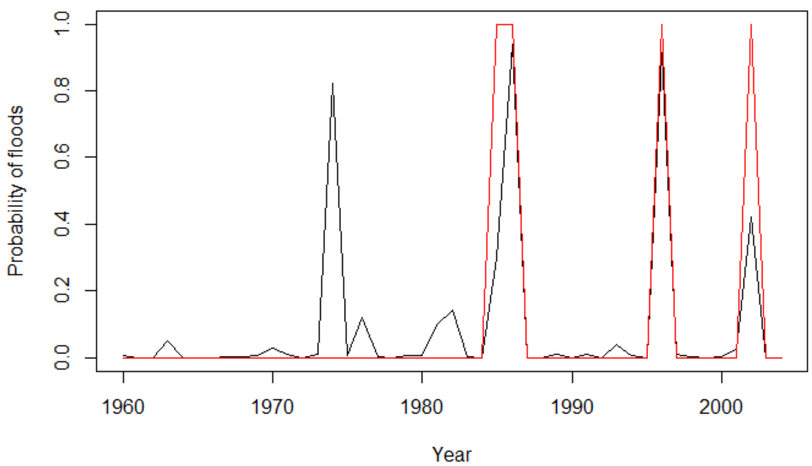



Figure C-13: Time series of observations and predicted values by the selected model for the 90 percentile data.

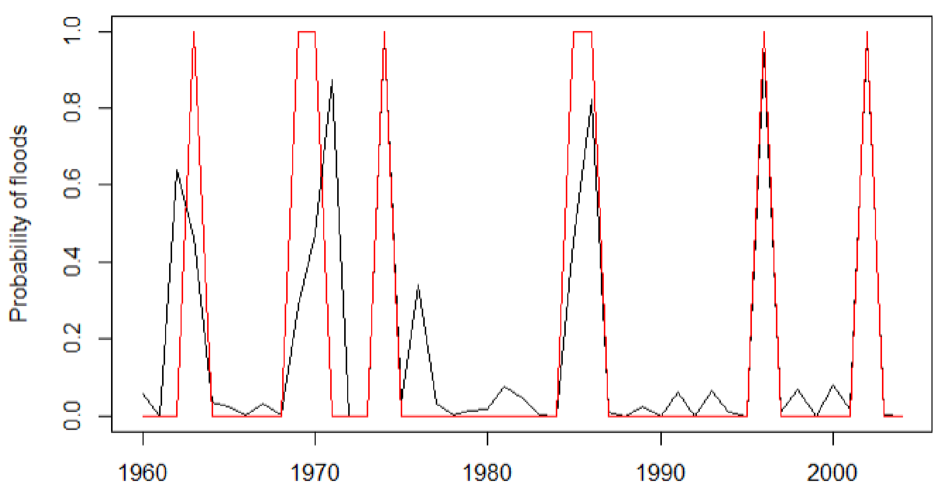



Figure C-14: Time series of observations and predicted values by the selected model for the top 20 percentile data. [red and black lines are overlapped. needs to be fixed. for example, in 1974 and 2004]

Because the analysis using the local regression showed that the linear model was adequate, the logistic regression was also conducted to select predictors of rainfall amounts and water levels, using LASSO method. The thresholds for the logistic regression were the upper 10$^{th}$ and 20$^{th}$ percentiles of flooded areas. For the BWBD's data that recorded the 10th percentile as floods, the best predictors were the maximum water levels in Rajshashi and Bhair Bazar, which were consistent with the results of the previous local regression. For the BWBD's data that recorded the 20th percentile as floods, the maximum rainfall amounts for the 3-day and 30-day windows and the maximum water level in Bhairab Bazar were selected as the best predictors.