A temporal and spatial analysis of China's infrastructure and economic vulnerability to climate change impacts

Xi Hu

Environmental Change Institute, University of Oxford

Dissertation presented for the degree of Doctor of Philosophy at the University of Oxford

College: St Antony's

Oxford, October 2017

Acknowledgements

Before starting a DPhil, I did a mental exercise that went through all the worst plausible scenarios – and terrified me. I carefully planned solutions for each scenario. Five years on, nearing the finish line, I realised that I needn't have, because of the people I have met at Oxford and beyond, many have whom turned into friends whom I shall treasure for the rest of my life.

First and foremost, I would like to thank my supervisor Jim for willing to take a risk with me, guiding me, supporting me patiently for the last five years and never losing faith in me. I still remember clearly at the first ITRC meeting, colleagues questioned how infrastructure could be studied in China with such sparse literature and data. Jim responded, "This is a pilot study we are undertaking and let's see where we can go with this". I suddenly felt a duty to deliver. On that day, I made a list of deliverables for the DPhil and am pleased to say that I have completed most of them, and have in some cases, gone beyond what was required.

I would like to thank my colleagues for helping me along the way. I am especially grateful for Raghav, who spotted mistakes in my papers, worked patiently with me to correct them and encouraged me endlessly. Despite all this, he still seems fond of the work. Many thanks to Wee Ho for teaching me hydrology and doing the Cama-flood model. Scott, Matt, Mike and Miriam have offered much wisdom and it was great fun working for ITRC on the energy demand model. Thanks to Simon Abele for helping out with assembling the rail track data and teaching me web scrapping techniques. I also much appreciate Sue and Jo's help with many practical things.

My two families, both Chinese and English, have been extremely patient with me. Wenwen, Andy, Jingles and Pablo are family whom I look to for comfort and guidance in times of difficulty. Valerie and David are amazing friends who have proofread my work many times. I am also grateful for an amazingly supportive DPhil group: Gonzalo, Michael, Edo, Yin, Xiawei, Janet, Lily, Xuanyi, Homero, Robert, Rafa, Yingqi among many others.

“功夫不负有心人” – my favourite Chinese proverb, meaning “nothing is impossible for a willing heart.” I am very fortunate to have had so many people to help me keep going and encourage me to pursue my dreams.

TABLE OF CONTENTS

Publications

Chapters of the thesis have been published or submitted to the following peer-reviewed journals:

- Hu, X., Hall, J.W. and Thacker, S. (2014) Too big to fail? the spatial vulnerability of the Chinese infrastructure system to flooding risks, in: Second International Conference on Vulnerability and Risk Analysis and Management (ICVRAM) and the Sixth International Symposium on Uncertainty, Modeling, and Analysis (ISUMA). *Vulnerability, Uncertainty and Risk*: 704-714.
- Hu, X., Hall, J.W., Shi, P. and Lim, W-H. (2015) The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*, 80(2): 1083-1118.
- Hu, X., Pant, R., Hall, J., Surminski. S (2017) Multi-scale assessment of the economic impacts of flooding on the Chinese manufacturing sector: firm to macro level analysis. Submitted to Risk Analysis.
- Hu, X., Pant, R., Lim, W., Lu, X., Hall, J. (2017) Variability of flood exposure in China's infrastructure systems in the context of a changing climate. Submitted to Nature Climate Change.
- Hu, X., Hall, J.W. (2017) China's Infrastructure (R)evolution: Exploring the Drivers of Infrastructure Development. Submitted to International Journal of Urban and Regional Research.

Abstract

A warmer climate is expected to increase the risks of natural disasters globally. China is one of the hotspots of climate impacts since its infrastructures and industries are often hard hit. Yet little is known about the nature and the extent to which they are affected. This thesis builds novel system-of-systems risk assessment methodologies and data for China, representing infrastructures (energy, transport, waste, water and digital communications) as interdependent networks that support spatially distributed users of infrastructure services. A unique national-scale geo-spatial network database containing 64,834 existing infrastructure assets is assembled. For the first time, flood and drought exposure maps of China's key infrastructures are created, highlighting the locations of key urban areas to understand how its infrastructures and population could be exposed to climate impacts.

To deepen the understanding of how climate change will affect the Chinese infrastructure system and hence its economy, economic impact modelling is applied. The research combines a detailed firm-level econometric analysis of 162,830 companies with a macroeconomic input-output model to estimate flood impacts on China's manufacturing sector over the period 2003–2010. It is estimated that flooding on average reduces firm output by 3.18%–3.87% per year and their propagating effects on the Chinese macroeconomic system to be a 1.38% – 1.68% annual loss in total direct and indirect output, which amounts to 17,323–21,082 RMB billion. Several infrastructure sectors – electricity, the heat production and supply industry, gas production and supply, the water production and supply industry – are indirectly affected owing to the effects of supply chain disruptions.

Taking the above analysis one step further, this thesis explores how climate disaster risks may change over the period 2016–2055, using flooding as a case study. A global river routing (CaMa-Flood) model at a spatial resolution of 0.25° x 0.25° is applied and downscaled for China, using the daily runoff of 11 Atmospheric and Oceanic General Circulation Models (AOGCMs). Combining the flood analysis with the infrastructure

database, this research demonstrates the changing locations of exposed infrastructures and their dependent customers. We find that by 2055, the number of infrastructure assets exposed to increasing probability of flooding under RCP 4.5 are 41, 268, 115, 53, 739, 1098, 432 for airports, dams, data centres, ports, power plants, rail stations, reservoirs respectively – almost 8% of all assets for each sector. The lengths of line assets exposed to increasing flood hazards are 14,376 km, 32,740 km, 102,877 km and 25,310 km oil pipelines, rail tracks, roads and transmission lines respectively. Under RCP 8.4, the numbers increase to 51, 301, 137, 71, 812, 1066, 424 for point assets. Linear assets increase to 19,938 km, 39,859 km, 122,155 km and 30,861 km. Further, we demonstrate that indirect exposure of customers reliant on those infrastructure assets outside the floodplain could also be high. The average number of customers affected by increasing flood probabilities are 54 million, 114 million and 131 million for airports, power plants and stations respectively. However, within this aggregate increase there is large spatial variation, which has implications for spatial planning of adaptation to flood risk to infrastructure. This is a first substantial study of flood impacts to infrastructure both in terms of direct exposure and their indirect implications.

Lastly, to shed some light on the potential vulnerability of China's infrastructure system to climate impacts, this thesis develops a framework that identifies the drivers of infrastructure development in China using evidence from policy documents and a unique geospatial dataset for the years 1900– 2010. Understanding these drivers will provide a useful foundation for future research in terms of developing infrastructure models that could project the locations of future infrastructure assets and networks in China, thereby quantifying how China's infrastructure exposure and vulnerability will change over time. Overall this research provides an integrated system-of-systems perspective of understanding network and economic vulnerabilities and risks to Chinese energy, transport, water, waste and digital communication infrastructures due to climate change. This is crucial in informing the long-term planning and adaptation in China.

Key words: Exposure · Flooding and Drought · Infrastructure (energy, water, waste, transport and digital communication) · Historical and spatial infrastructure development · Climate Change · Disaster impact assessment · Input Output Analysis · Econometrics · China ·

List of figures

List of tables

1. Introduction

1.1. Background

China used more concrete in 3 years (2011–2013) than the U.S. used in the entire 20th century. Much of this was for building infrastructure (Swanson 2015). Between 2011 and 2015, investment in fixed assets, including transport, energy and digital communication, grew from 31 RMB trillion to 56 RMB trillion (National Bureau of Statistics of the People's Republic of China 2016). Yet, it plans to build more both internally and abroad, with the help of its newly established Asian Infrastructure Investment Bank and the Belt and Road Initiative, which has pledged investment of $1 trillion.

While infrastructure investment is generally believed to be beneficial to the economy, infrastructure systems are vulnerable to extreme climate impacts and the rapid pace of growth may be locking in unmanageable risks. Indeed, flooding in 2014 in China could be a foretaste of the disruption that is expected to intensify in a changing climate. 62 rail links and 33,569 roads were disrupted (as opposed to 28 and 33,569 respectively in 2011), while events resulted in the failure of 14,316 electricity transmission lines (as opposed to 8,516 in 2011), prompting the shutdowns of factories and cutting off power to millions of households (Ministry of Water Resources 2014b; Ministry of Water Resources 2011b). Drought, on the other hand, resulted in water shortages, threatening the water supply to millions of households (Ministry of Water Resources 2014). It also disrupted shipping routes and significantly reduced water quality in reservoirs (*Ibid*).

Not only infrastructure is affected. Floods have cost many companies output, and disrupted supplies and distribution as well as affecting millions of people and the wider economy. Between 1900 and 2011, China suffered 207 recorded flood events, which cumulatively affected 1.8 billion people (Chen et al. 2013). In 2016, the manufacturing purchasing managers' index fell significantly due to heavy rains and flooding in most of China's provinces which impacted production and transportation among other things (Lockett 2016).

Although climate change and the rapid rate of infrastructure development over the past few decades are expected to increase the vulnerability of China's infrastructure system and economy to the impacts of these hazards, we have very limited understanding of the nature of this vulnerability, yet this is crucial for adaptation decision making. It is especially important for China, which is now the largest infrastructure investor in the world and a key player in the global supply chain.

1.2. Aims and objectives

The objectives of this research are thus to understand how the Chinese infrastructure system, its industries and economy could be potentially vulnerable to climate change impacts. We will focus on flooding and drought as these resulted in some of the highest economic impacts among all natural disasters that occurred in China between 1990–2014 (The United Nations Office for Disaster Risk Reduction 2017). Specifically, this research seeks to answer the following questions:

1. How is the Chinese infrastructure system spatially exposed to flooding and drought hazards?
2. What are the impacts (direct and indirect) of flooding on Chinese businesses, industries and the economy? How are infrastructure sectors affected?
3. How will these impacts change in the future in the context of climate change?

Before proceeding further, we will define what we mean by infrastructure system. Owing to the absence of a single comprehensive, functional and practical meaning of infrastructure (Baldwin & Dixon 2008; Torrisi 2009), it is difficult to agree upon a universal definition. Nevertheless, we defined an infrastructure system as a "collection and interconnection of all physical facilities and human systems that are operated in a coordinated way to provide a particular infrastructure service" (Hall et al. 2016). Here are our definition is applied to the five infrastructures – energy, water, waste, transport and digital information. In this thesis, we take a taxonomy approach of defining the infrastructure system of consisting of five sub-systems:

- Energy systems, including electricity, gas and liquid fuel networks;
- Transport systems, including road, rail, ports and airports;
- Water supply;
- Wastewater and solid waste treatment and disposal;
- Data storage/processing infrastructure.

1.3. Chapter outline

Chapter 2 discusses the relevant literature for this research and identifies the major gaps. Chapter 3 outlines the methodology used in this thesis and summarises the contributions made. Chapter 4 demonstrates a conceptual framework for understanding the infrastructure system in China, building on the work of the UK Infrastructure Transitions Research Consortium (UK ITRC). It provides a spatial distribution of infrastructure assets and networks in five sectors (energy, water, waste, transport and digital communication) and develops a methodology that calculates the potential number of customers affected should infrastructure assets fail owing to one or a series of flooding event(s), for the rail and electricity sectors. Chapter 5 builds on chapter 4, refines the methodology and extends the analysis to aviation, shipping and wastewater sectors for both flood and drought hazards. Chapter 6 examines the economic impacts of flooding on Chinese businesses, industries and the broader economy. It uses a combination of econometric and input-output analyses to quantify the economic consequences of disruption to manufacturing firms due to flooding and the associated systemic propagating indirect effects on the Chinese economy.

Looking into the future, chapter 7 investigates the effects of climate change on flooding risks by driving a global river routing (CaMa-Flood) model, using the daily runoff of 11 Atmospheric and Oceanic General Circulation Models (AOGCMs). It analyses how the Chinese infrastructure stock will face changing flood hazards and estimates the number of customers potentially affected. Chapter 8, on the other hand, studies the ways in which infrastructure stocks may evolve into the future by looking for lessons from the past. It builds a framework that identifies the drivers of infrastructure development in China using evidence from policy documents and a unique geospatial dataset for the years 1900 –2010. Understanding these drivers provides a useful foundation for future research, which could be used for developing infrastructure models that project the locations of future infrastructure assets and networks in China, thereby quantifying China's changing infrastructures' exposure and vulnerability over time. Chapter 9 concludes and discusses some of the implications for this research.

2. Literature Review

Here we briefly describe the relevant literature strands for this research, which span several disciplines – engineering, geography and economics. We will separate the literature review into: vulnerability and exposure studies to natural hazards (flooding and drought); infrastructure risk assessments in the context of natural hazards; economic impact assessments of natural hazards; infrastructure development theories and models; and climate change and infrastructure modelling.

2.1. Vulnerability and exposure studies to flood and drought hazards

Studies of vulnerability and exposure to natural hazards sit within the literature on natural disaster risk reduction. The IPCC SREX report, Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, defines risk to natural disaster as a function of hazard, exposure and vulnerability (IPCC 2012b). In particular, flood risk is commonly defined as the product of the probability of flooding and the consequential damage, summed over all possible flood events (Hall et al. 2005). The probability of flooding is typically derived from some hydrological modelling based on meteorological fields, analyses of extreme value statistics that calculate different return periods, and inundation modelling that estimates flooding depths for a given geographical unit (Ward et al. 2013). The consequential damage is conventionally evaluated by some economic impact modelling, for instance, by adopting indicators that show the affected population, GDP, and/or exposed urban asset values (*Ibid*).

Drought, on the other hand, is the result of many composite factors, such as high temperatures, high winds, low relative humidity, and the timing and characteristics of rain (Mishra & Singh 2010). Capturing drought risk of a probabilistic nature is difficult because of the complexity of the factors involved; therefore several indices have been developed that characterise different aspects of drought risks. Prominent examples of drought indices include the Standardised Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Crop Moisture Index, the Surface Water Supply Index, the Vegetation Condition

Index, and the Standardised Runoff Index (*Ibid*). Some indices, such as the SPI, only focus on precipitation, whereas others, such as PDSI, may incorporate variation in temperature, soil moisture, reservoir storage, streamflow, and snow pack (*Ibid*).

Risk-based studies are ideal because they are probabilistic assessments of possible future hazard events and their impacts (Li et al. 2012; Wu et al. 2012). Unfortunately, much of the literature has not been able to determine the probability quantitatively owing to the huge uncertainties involved and a lack of data. As such, most relevant literature for our study concerns exposure and vulnerability.

Overall, there are three main approaches used for understanding vulnerability and exposure, which are: qualitative, potential consequences and impact assessment. Qualitative approaches are the first generation of vulnerability studies. These are often derived from surveys and interviews, which are sufficient for obtaining a general idea of the possible vulnerabilities and particularly useful for understanding the decision-making process (De Sherbinin et al. 2007; Regmi & Hanaoka 2011; Zarafshani et al. 2012). However, they remain largely descriptive and hard to compare across systems.

Potential consequence approaches assess the vulnerability of a system to natural hazard impacts by looking at how the system may be affected if hazards occur (HSBC 2011; IPCC 2012a; Wilhelmi & Wilhite 2002; Lewis 2009; Dutta et al. 2003). Finally, impact assessment approaches examine how a system has been affected by natural disaster events, in contrast to potential consequence approaches, where vulnerabilities are based on how a system may cope given the possibility of future natural hazards, often measured by population or economic impacts (World Bank 2004).

2.2. Infrastructure risk assessment

Assessments of risks to infrastructure systems, which may or may not originate from natural disasters, have been in existence for a while (Mao et al. 2009; Erath et al. 2009; Marrone et al. 2013). In the context of natural disasters specifically, many have looked at how infrastructure systems may be vulnerable to hazards by examining how to maintain reliability given certain damage scenarios, using a variety of methods, such as reliability and risk analysis, network science, inoperability input-output models and failure stress-testing (Pant et al. 2016; Arvidsson et al. 2015; Thacker, Barr, et al. 2017).

For China, infrastructure risk assessment is similarly derived mostly from the civil engineering field, using reliability and safety models, among others – although some recent studies have looked at the vulnerability of Chinese infrastructure from a network perspective (Wang et al. 2013; Ouyang et al. 2009; Mao et al. 2009). Literature concerned with infrastructure vulnerability due to flooding and drought impacts in China – most of which resides in the "potential consequences" domain – is scarce. Two examples are those of Xie and his fellow researchers, and of HSBC (Xie et al. 2013; HSBC 2012).

2.3. Economic impacts of natural disasters

Not only the physical system such as infrastructure assets and networks is affected by natural disasters; businesses and the economic system are also impacted. Estimating the impacts is not straightforward however. In the current literature, there is no consensus about the definition of 'impacts' (see Penning-Rowsell et al. 2003; Merz et al. 2010; Kreibich et al. 2014; Meyer et al. 2013; Kousky 2014). A common framework in the literature classifies impacts into five categories: (1) direct costs – those incurred due to physical damage to assets due to susceptibility to flooding; (2) business interruption costs – those incurred in hazard areas when people are not able to carry out their work because their workplace is either destroyed or made inaccessible; (3) indirect costs – the costs incurred inside or outside hazard areas with a time lag, when, for instance, there are production losses to suppliers and customers of the companies that suffer direct or business interruption losses; (4) intangible costs – types of damage that are not easily measurable in monetary terms such as environmental impacts, health impacts and impacts on cultural heritage; and (5) risk mitigation costs – any costs attributed to the operation, maintenance, research and development of risk mitigation infrastructure, or other measures for the purposes of risk mitigation; or any secondary costs (externalities) occurring in economic activities or localities that are not directly linked to such infrastructure investment (Kreibich et al. 2014; Meyer et al. 2013).

It should be noted that business interruptions fall in a grey area. Some include business costs within direct costs (Merz et al. 2010), whereas others account them as indirect costs (Carrera et al. 2015; Kousky 2014; Rose & Liao 2005). Similarly, intangible costs and risk mitigation costs are sometimes not explicitly classified and may be accounted as direct or indirect impacts (Kousky 2014).

2.4.1. Methods for assessing economic impacts of natural disasters

A range of different methods have been developed to assess the economic impacts of natural disasters that include flooding (see Table 1). These methods primarily focus on estimating direct and indirect economic losses, with other effects included within these two categories. A particularly common approach for estimating direct damage losses is event analysis – both ex-ante and ex-post – which uses empirical and qualitative approaches to create damage-curves for general classes of residential or business buildings, equipment, and inventory stocks for different levels of flooding (depth or discharge) to estimate economic impacts of flooding events (Tierney & Nigg 1995; Kreibich et al. 2007; Molinari et al. 2014; Ayyub et al. 2012). Event analysis model outputs are generally useful inputs for other models that estimate direct and indirect losses.

Table 1. A summary of methods available to assess the economic impacts of natural disasters

Method	**Spatial scale**	**Scholarly works**
Event analysis	Individual, firm, sector	Tierney & Nigg 1995; Suarez et al. 2005; Kreibich et al. 2007; Molinari et al. 2014; Kreibich et al. 2010; Ayyub et al. 2012
Computable General Equilibrium (CGE)	Global and national	Rose & Liao 2005; Mechler et al. 2010; Carrera et al. 2015
Input-output (IO) analysis	Global/National/ regional	Van Der Veen & Logtmeijer 2005; Crowther et al. 2007; Yamano et al. 2007; Hallegatte 2008; Jonkman et al. 2008; Pérez & Barreiro-Hurlé 2009; Rose & Wei 2013; Hallegatte 2013; Jenkins 2013
Econometric techniques	All	Raschky 2008; Craioveanu & Terrell 2009; Hochrainer 2009; Schumacher & Strobl 2011; Vu & Noy 2013; Yamamura 2013; Coelli & Manasse 2014; Kocornik-mina et al. 2015

Amongst the methods most widely used for estimating direct and indirect economic flow losses are Computable General Equilibrium (CGE) and Input-Output (IO) based approaches, which work at macro scales. CGE models have been used for disaster impact analysis because they are able to model non-linearly the behavioural response to price changes, input and import substitutions and supply constraints (Rose & Liao 2005; Mechler et al. 2010; Okuyama & Santos 2014). CGE models capture indirect economic losses because they consist of a system of equations which describe the behaviour of the economic agents (representative household and firm), the structure of the markets and the institutions, and the links between them (Carrera et al. 2015). The IO-based models are linear models working on the premise that each industry produces goods and consumes goods from other industries in order to produce such goods, and thus is able to capture the interdependence of economic sectors upstream and downstream of the supply chain of the disrupted goods (Hallegatte 2008; Hallegatte 2014; Jenkins 2013). While traditional IO models have been critiqued for their linearity and simplistic demand-driven approach (Rose 2004), over the years several hybrid IO models have been developed to incorporate, among others, non-linearity, supply-side effects, and substitutions (Hallegatte 2008; Jenkins 2013; E. E. Koks et al. 2015).

Econometric techniques, which are statistical methods, are also widely used to estimate the impacts of natural disaster events, mostly at macro scales. These methods do not make a distinction between direct and indirect impacts, but instead concentrate on indicators of total economic activity such as GDP (Coelli & Manasse 2014). Most find a negative impact from disasters on the economy, the extent of which depends on the size of the shock, how strong the institutions are, and how diversified the economies are, as well as the length of time after a disaster, among other factors (Hochrainer 2009; Schumacher & Strobl 2011; Raschky 2008; Kocornik-mina et al. 2015). In terms of the time frame, econometric models studying the impacts of natural disasters are mostly based on economic growth/productivity both for the short run and long run whilst others look at the impact on individuals and firms (Hochrainer 2009; Coelli & Manasse 2014; Kocornik-mina et al. 2015).

2.4. Infrastructure development

Assessing how infrastructure systems will be affected by climate change is extremely challenging. Part of the solution involves understanding how different infrastructure assets and networks will grow in the future, not just in aggregate terms but also spatially; another part must take account of evidence from the past.

Different disciplines have developed their own respective theories/models for projecting future infrastructure growth. Building on Heinsz's analysis (Heinsz 2002), we note two strands of the most relevant discussions in infrastructure development: economic perspectives and political institutions and investment.

2.4.1. Economic perspectives

From a macro-economic perspective, infrastructure is often lumped with other forms of capital. A dominant strand of this literature is concerned with neoclassical growth models (e.g. Solow and Koopman), which explain long-run economic growth by looking at capital accumulation, labour or population growth, and technological progress. A key assumption in the short run is that capital is subject to the effects of increasing and diminishing returns in a closed economy. Early in the development process, network effects specialisation and economics of scale mean that the marginal benefits of infrastructure provision increase. Conversely, as the economy converges, returns on infrastructure investment diminish because of the high cost of infrastructure provision in dense urban settings and because later infrastructure investments are often aimed at dealing with congestion at peak times so utilisation at other times may not be high. These increasing and diminishing returns are often depicted as an S-shaped logistic curve whereby we see relatively low to moderate growth rates in the initial decades after the initial penetration of infrastructure services, followed by a rapid acceleration of growth and then a deceleration in mature economies.

Many economists have demonstrated an empirical association between growth and infrastructure (Canning 1997; Munnell 1992; Czernich & Falck 2009; Hou & Li 2011). Seminal work by Aschauer employed cross-sectional state-level data on gross state product and public infrastructure expenditure 1965 and 1983 and provided evidence that infrastructure investment was key to the economic "golden age" of the 1950s and 1960s (Aschauer 1990). Assessing 64 empirical papers, Straub found a positive and significant link between infrastructure and some development outcome (Straub 2008). However, while most agree that there is a correlation between economic growth and infrastructure development, the evidence for the direction of causality is unclear. Some scholars have found contradictory results if different measures of growth are applied. For example, Banerjee and others show that proximity to transportation networks has a moderately positive causal effect on per capita GDP levels across sectors, but no effect on per capita GDP growth (Banerjee et al. 2012). Results may also differ depending on the time effect: one would not expect the growth in the capital stock in one year to be correlated with the growth in output in the same year (Nadiri & Mamuneas 1994).

A range of economic models – namely New Economic Geography (NEG), Land Use Transport Interaction (LUTI) and Spatial Computable Generable Equilibrium (Spatial CGE) – have sought to explain the influence of infrastructure development on the spatial distribution of economic activities. NEG models predict empirically observed patterns of the core-periphery spatial structures and income disparities within a country, incorporating three endogenous processes – increasing returns to scale, transport costs and the movement of factors of production (Fujita 2010; Redding 2010). Land Use Transport Interaction models are often used to assess the economic impacts of transport investment on the property and labour markets. Infrastructure is modelled in terms of its effect on generalised costs of travel to work, or indirectly in the general attractiveness function for different locations. Spatial CGE models are spatial extensions of Computable General Equilibrium (CGE) models (Oosterhaven et al, 2001), which simulate entire economies through functions that describe the behaviour of economic agents operating in markets at equilibrium, and include infrastructure as transport networks that are incorporated as costs (Robson and Dixit 2005).

2.4.2. Political institutions and investment

Given the inevitable involvement of governments, to a greater or lesser extent, patterns of infrastructure development may be explained better by the political economy than by economic efficiency (Canning 1997). Political motives may include the provision of employment, the desire to improve services to key constituencies, concern over the limitations of private provision, a desire to urbanise and industrialise (Jacobson & Tarr 1995; Swyngedouw et al. 2002), and colonisation (for example, China and India's infrastructure development during their colonial era). Economic conditions play an important political role in the pattern of infrastructure investment (Heinsz 2002). For instance, the Tennessee Valley Authority (TVA), part of the New Deal charted by the US Congress in 1933, was motivated by political upheaval in response to the Great Depression (Culvahouse 2007). Environmental legislation has mandated standards for waste water treatment, disposal of solid waste and emissions from power plants and transport systems, leading to major investments in new and retrofitted infrastructure (Jacobson & Tarr 1995).

The state's role in ownership of infrastructure differs geographically through time and depending on the sector. The transition of infrastructure from fragmented pre-industrial arrangements to public hands happened at different times for different sectors and countries. For instance, reformers in late-nineteenth century England concluded that sanitation was too important an urban function to be left in the hands of profit-motivated contractors (Hering and Greeley in Jacobson & Tarr 1995). England accordingly developed a public urban network of sewers and waste treatment plants. In the Netherlands, wide economic-cultural-political transformations led the public authorities, who initially preferred leaving waste treatment to the private sector, to invest in piped water infrastructure (Geels 2005). Late industrial eras meanwhile have been characterised by a shift back to private ownership, driven by public debt (i.e. the desire to raise revenue by selling public assets and shift new investments off the public balance sheet) and/or focus on privatisation as a means to increase efficiency at a time of otherwise decreasing returns to infrastructure investment.

2.5. Climate change and changing vulnerability

2.5.1. Climate change and natural hazards

It is well known that a warmer climate may increase the risks of natural disasters globally (IPCC 2007; IPCC 2012a; Hirabayashi et al. 2013). As our climate chapter is focused on flooding, here we only discuss climate exposure studies related to this hazard.

Most climate literature has examined increasing/decreasing risks by studying the changing exposure of people and/or economies under different climate scenarios. For instance, the global exposure to river and coastal flooding, on the basis population density and GDP per capita, is estimated to be 45 trillion USD in 2010 and would increase to 158 trillion USD in 2050 (Jongman et al. 2012). The largest absolute exposure changes between 1970 and 2050 are in North America and Asia (*Ibid*). A more recent study projects that by 2050 the range in increased exposure across 21 climate models under SRES A1b will be 31–450 million people and 59 to 430 thousand km^2 of cropland, and the change in risk will vary between −9 and +376 % (Arnell & Gosling 2016). Focusing on the hydrological cycle alone and using 11 climate models, Hirabayashi and colleagues demonstrated a large increase in flood frequency in Southeast Asia, Peninsular India, eastern Africa and the northern half of the Andes whereas in other certain areas of the world, flood frequency is projected to decrease (Hirabayashi et al. 2013).

2.5.2. Climate change and infrastructure

To date, very few studies have looked at infrastructure exposure to changing climate risks. Climate change could, however, have huge impacts on infrastructure systems and networks, for example, by affecting the energy demand of buildings or changing water supply (Christenson et al. 2006; Guo et al. 2002).

China is no exception to these threats. The second Chinese National Climate Change Impact Assessment Report (CNCCIA) documents the major climate change impacts on the infrastructure system, which include the effect of sea-level rise on major engineering projects such as the North-South water transfer scheme, and heat-wave/permafrost/windstorm damage to the transport network. In particular, flooding is highlighted as severe impacts spanning the major strategic infrastructure sectors such as energy, transport and water (Lin et al. 2007). Evidence from other parts of the world suggest that infrastructure will be affected by systemic and cascading climate risks, which are apparent in the water, sanitation, energy, transport, and communications sectors, owing to the often tightly coupled character of urban infrastructure systems (see Rosenzweig and Solecki, 2010, in Revi et al., 2014).

3. Methods and data

The research methodology will focus on three main components: infrastructure modelling, hazard modelling, economic impact modelling (Figure 1). The approach is specifically designed to answer the three questions raised before:

1. How is the Chinese infrastructure system spatially exposed to flooding and drought hazards?
2. What are the impacts (direct and indirect) of flooding on Chinese businesses, industries and the economy? How are infrastructure sectors affected?
3. How will these impacts change in the future in the context of climate change?

Before we discuss the methodology in detail, we will provide the requirements for the data first. The main four sources of the dataset we obtain are: a. historical flood data (1985-2015); b. time series and geospatial infrastructure database; c. firm-level data in China; d. macroeconomic input-output table for China.

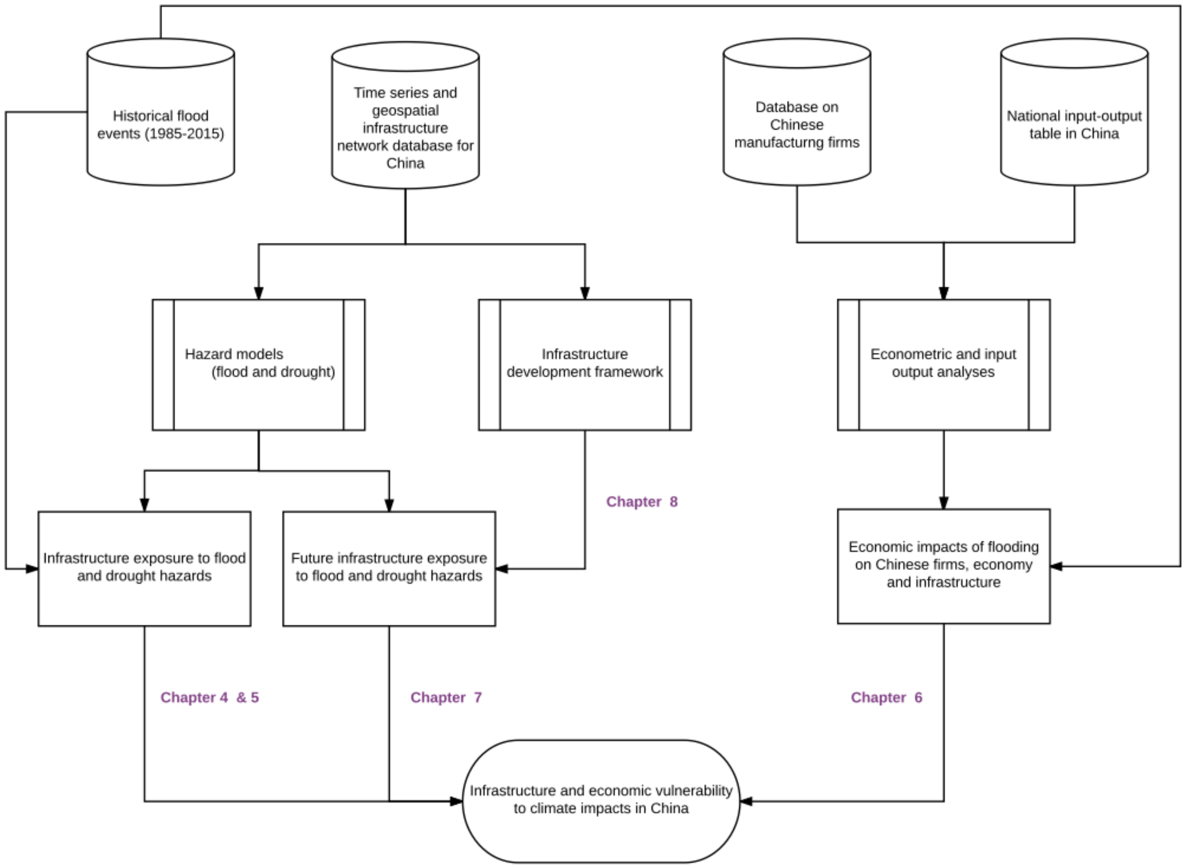


Figure 1. Thesis methodology

3.1. Data requirements

3.1.1. Infrastructure database

To understand infrastructure exposure and vulnerability to flooding and drought in China, we must formulate a way of understanding what we mean by infrastructure. We follow the UK Infrastructure Transitions Research Consortium (UK ITRC) (Hall et al. 2012) in defining infrastructure as an integrated system consisting of five sectors – energy, transport, water, waste and ICT. Within each of these sectors, we identify a few sub-sectors that contain a range of different infrastructure assets. This taxonomy approach allows us to systematically examine changes in exposure and vulnerability to hazards because the assets remain the same. Overall, we establish a network-based dataset, which contains a total number of 17,339 nodes and 7,991 lines (chapter 4). We increase the number of assets to 64,834 as we move further into the research (chapters 4,5,6,7) and add a time dimension to all assets whenever feasible (chapter 8). This database spans the 21st century and represents a major part of the existing Chinese infrastructure assets that are potentially exposed to flooding and drought impacts [***research question 1; chapter 3 and 4 are used to address this objective***].

3.1.2. Chinese firm database

We obtain a large dataset on China's manufacturing sector, covering a total of 162,830 companies with detailed information on company name, firm revenues, number of employees and addresses between 2003 and 2010. The number of sectors included is 24 (see Table 12, chapter 6). We georeference the company dataset so that they can be matched with flooding records later.

3.1.3. Chinese input output table

We download the Chinese input output table for 2010 from the National Bureau of Statistics, which has the input output flows for 41 sectors.

3.1.4. Past flood events

Past flooding data are collected from the Dartmouth Flood Observatory, which contains an archive of large floods in the world between 1985 and 2016 (Brakenridge 2016). We filter all events in the database between 1985-2016 to conduct the analysis in chapter 4. The flood sample in this study consists of major reported flooding events in China. These are "derived from a wide variety of news and governmental sources", and are divided into three classes – large, very large, and extreme (*Ibid*). A further record of 128 major floods in China is selected for the period between 2003 and 2010 for analysis in chapter 6.

3.2. Infrastructure exposure to flooding and drought hazards

3.2.1. Flood and drought hazard modelling

To understand how China's infrastructure is exposed to current flood and drought hazards, we use flood and drought data hazard models. For flooding, we first apply historical data of flood records to identify regions exposed to flooding hazards. This way, we are able to locate areas where infrastructure assets are potentially exposed to these hazards. Later on, we make use of a global river routing model called the Catchment-Based Macro-scale Floodplain (CaMa-Flood) model to prepare the flood hazard map (Yamazaki et al. 2011). This is because it is based on hydrological modelling that routes the runoff input simulated by a land surface model into the oceans or lakes along a prescribed river network, and uses longer historical records as part of its validation process. Although it is a global model, which had to be downscaled, it is better than any national-scale assessments currently available in China. For drought, we work with collaborators in China who compiled a hazard map based on precipitation, and the sensitivity of land use (Shi 2011) [***research question 1; chapter 5 is used to address this objective***]. Historical records of floods and drought are used to validate the results from the hazard models.

3.2.2. Infrastructure hotspots

To go beyond simply identifying where infrastructure assets might be exposed to flooding and drought hazards, we develop a suite of models assigning the number of users to individual infrastructure assets. This way we begin to distil some of the potential impacts from flooding and drought if individual assets fail i.e. on a local level. For point assets, we firstly assign customers based on a Voronoi diagrams that define areas according to the locations of individual infrastructure assets (chapter 4). These areas are closer to each individual asset within it than outside it. We then intersect the Voronoi diagram with population data which gives the number of customers in that area and subsequently redistribute the customers for every Voronoi diagram in a way that seeks to have roughly equal populations per unit of capacity (chapter 4). In a later stage of this research, we obtained actual capacity and usage data for each asset (for example, power plants, waste treatment plants), and thus modified our models based on these parameters so that the number of customers allocated to each asset represents reality better (chapter 5).

We then translate the local-level exposure to broad-level analyses using the concept of "hotspot analysis" by applying the Kernel density estimator. We define an infrastructure criticality hotspot as a geographical location where there is a concentration of critical infrastructure, measured according to the number of customers directly or indirectly dependent on the infrastructures in that location. The Kernel density estimator is a nonparametric statistical method for estimating the density of data and it is useful because it provides us with a spatial understanding of how infrastructure hotspots – where users are concentrated – might be exposed to flooding and drought impacts [***research question 1; chapters 4 & 5 are used to address this objective***].

3.3. Economic impacts

As previously mentioned, not only the physical system such as infrastructure assets and networks is affected by natural disasters; businesses and the economic system are also impacted. This research empirically estimates the impact of past flooding events on

Chinese businesses in the manufacturing sector and develops a methodology to quantify the broader impact on the economy. It uses a combination of econometric and input-output analyses [***research objective 2; chapter 6 is used to address this objective***].

3.4. Changing exposure and vulnerability for Chinese infrastructures and networks

Looking into the future, we seek to understand two aspects of potential change: one on the climate side, the other on the infrastructure side [***research objective 3; chapters 7 & 8 are used to address this objective***].

On the climate side, we drive a global river routing model – the Catchment-Based Macro-scale Floodplain (CaMa-Flood) – using the daily runoff of the Atmospheric and Oceanic General Circulation Models (AOGCMs) at a spatial resolution of 1° x 1° (chapter 7). For the AOGCMs, we adopt a historic (1970–2005) and future period (2006–2100) at representative concentration pathways (RCP) 4.5 and 8.5. From the daily river-routing outputs, we extract the annual maxima value of the river water depth (spatial resolutions: 0.25° x 0.25°) for each AOGCM (1970-2100 (131 years) or 1970-2099 (130 years). This way, grids with higher river water depth are associated with a higher level of flooding hazard.

To examine how China's infrastructure assets and networks are exposed to changing flooding probabilities due to climate change, we use the results from the aforementioned CaMa-Flood model for RCP 4.5 and RCP8.5 at return periods 30, 50 and 100 respectively. Based on these results, we compute how probability of flooding may change for specified geographical locations in China and superimpose the infrastructure assets and network database we collected. This way, we are able to pinpoint the exact infrastructures that face increasing, decreasing or non-changing flooding hazards due to climate change. Further to this analysis, we calculate the number of customers each infrastructure asset serves, according to population and data usage data. As such, we not only show those potentially vulnerable infrastructures but also the people who are dependent on them yet may not necessarily live in the floodplain.

On the infrastructure side, we investigate how this exposure may change over time as China continues to urbanise. We study how the Chinese infrastructure system has evolved over the past few decades by studying the Chinese Five-Year Plans between 1980–2015 and collecting empirical time series evolution data [***research objective 3; chapter 8 is used to address this objective***]. With this empirical dataset, we develop a framework that explains the drivers of the infrastructure development trajectory in China. This work can be used as a basis to build an infrastructure development model that projects into the potential locations of future assets and networks, thereby quantifying changing exposure to climate-induced hazards.

4. Too Big to Fail? The Spatial Vulnerability of the Chinese Infrastructure System to Flooding Risks

4.1. INTRODUCTION

China is historically vulnerable to flooding. In particular, its infrastructure system is often hard hit by these events. According to the Ministry of Water Resources, the 2011 floods alone resulted in the interruption of services to 28 rail lines, 21,961 roads, 49 airports and the failure of 8,516 electricity and 9,734 communication lines (Ministry of Water Resources 2011a).

In order to avoid these losses, understanding infrastructure vulnerability is crucial. A first order assessment of vulnerability to hazards such as floods can be constructed by assessing the people and economic assets exposed to those hazards, however, these assessments are not helpful for targeting surveillance and investments for infrastructure development because they often do not possess a spatial understanding of infrastructure assets, nor are they flexible enough to be applied to relevant scales. In this paper, we demonstrate a methodology that is capable of understanding this spatial aspect of the vulnerability for the Chinese infrastructure system to flooding impacts on both a broad and local scale. With our local-scale analysis, we are able to allocate a number of customers to each infrastructure asset at the plant level. On the broad scale, we establish a spatial database of the Chinese infrastructure system and identify critical infrastructure hotspots – defined as a geographical location where there is a concentration of critical infrastructure, measured by the number of customers dependent on those infrastructures.

The outline of the paper is as follows. Section 4.2 provides the conceptual framework we adopt in understanding the infrastructure system and spatial maps of infrastructure asset locations. Section 4.3 describes our methodology for allocating customers to each infrastructure asset on the local scale, and how we conduct hot-spot analysis to flooding risk on the broad scale. Section 4.4 discusses some preliminary results, implications and possibilities for future work.

4.2. Infrastructure vulnerability in China

The Chinese infrastructure system is complex, extensive and consists of many sub-categories of dense networks. We define the infrastructure system as an integrated system consisting of five sectors – energy, transport, water, waste and digital communication (Hall et al. 2012). Within each of these sectors, we identify a few sub-sectors that contain a range of different infrastructure assets (see Table 2). Overall, we establish a network-based dataset, which contains a total number of 17,339 nodes and 7,991 lines. This database represents a major part of the existing infrastructure assets that are potentially vulnerable to flooding impacts. All data collected here are derived from publicly available datasets and crosschecked with other sources – business and government – whenever possible. Some sectors have more complete dataset than others. Energy networks for example, are deemed sensitive in China and are not disclosed publicly. Geo-located port information was not accessible. Digital communication networks and data centres are privately-owned thus difficult to collect for the whole country. Transport (except ports), water and waste datasets are more complete because they are publicly available or can be obtained from a variety of business and government sources. Nevertheless, for all infrastructure sectors except digital communication, we have included the major assets and networks where most of the demands are concentrated.

Table 2. Infrastructure asset datasets

Sector	Sub-sector	Asset type	Description
Energy	Electricity	Power plants	Total of 2116 nodes including 1331 power plants and 785 substations
		Transmission network	846 power transmission lines

	Natural Gas, Liquid and Solid Fuels	Pipelines	156 completed pipelines including crude oil, natural gas, produced oil
Transport	Roads	Road network	2725 lines and 2198 nodes
	Rail	Rail tracks	2863 tracks
		Stations	5401 train stations
	Shipping	Ports	155 ports
		Waterways	59 Inland waterways
	Aviation	Airports	146 existing airports
Water	Water supply	Reservoirs	3140 reservoirs
		Dams	770 dams
		Rivers	1342 rivers
Waste	Waste water	Waste treatment	2743 waste water treatment works
	Solid waste	Landfill sites	286 waste treatment plants/ landfill sites
ICT	Mass data and computation facilities	Telecoms	384 Data centers

Figure 2 provides a visual representation of parts of the Chinese energy network that are subject to potential flooding impacts. Broadly speaking, we observe that for substations, vulnerability is more clustered along the coast; for the power plants, vulnerability is more evenly distributed. Although our transmission network, which runs 118,178 km, only shows approximately 9% of the total transmission network length (1,337,000 km above 35 kV), it arguably represents the most critical lines as they carry the highest voltages (220 – 500 kV) (China Electric Power Yearbook Editorial Committee 2011). Regarding the Chinese natural gas network, we cover 37,175.4 km out of the total 40,000 km (National Energy Administration 2012). Indeed, we observe the nationally planned morphology of the natural gas network – “Western gas transported towards the east i.e. the blue lines in Figure 2; northern gas moving down south i.e. the dotted blue lines”. We also demonstrate that currently 65,041.4 km of completed natural gas and liquid fuel pipelines are potentially vulnerable to flooding impacts, and a further 25,267.4 km of planned pipelines can also be vulnerable in 2030.

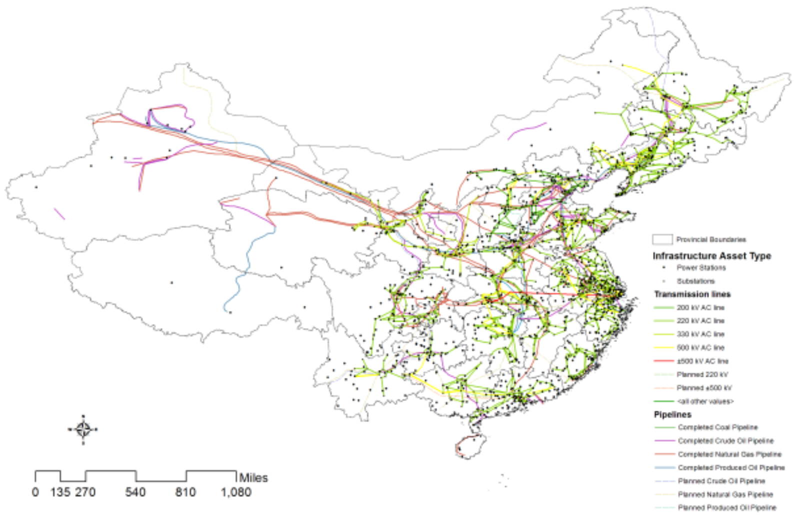


Figure 2. The Chinese Energy Network

Source: Harvard ChinaMap, Carbon Monitoring for Action (CARMA) and CNTEN.Ltd

Figure 3 depicts a dense network of vulnerable transport assets. The total lengths for the road, rail and inland waterway networks in our dataset are 545,506.4 km (13.6% of the total), 90,244.7 km (92% of the total) and 17,737.4 km (14.3% of the total) respectively (Ministry of Transport 2011; Ministry of Rail 2012). Within the road network, the total lengths of highway, national roads and other major roads are 63,370.2 km (85.5% of the total), 118,148.4 km and 363,987.9 km respectively (Ibid). The plan to construct "Five vertical and seven horizontal" national trunk roads is also evident in Figure 3. Regarding aviation, we have locationasl data on 146 of the 183 Chinese civil airports (Civil Aviation Administration of China 2013). Unfortunately we only have data on 155 out of the 5453 coastal ports and 59 major inland waterways (Ministry of Transport 2011).

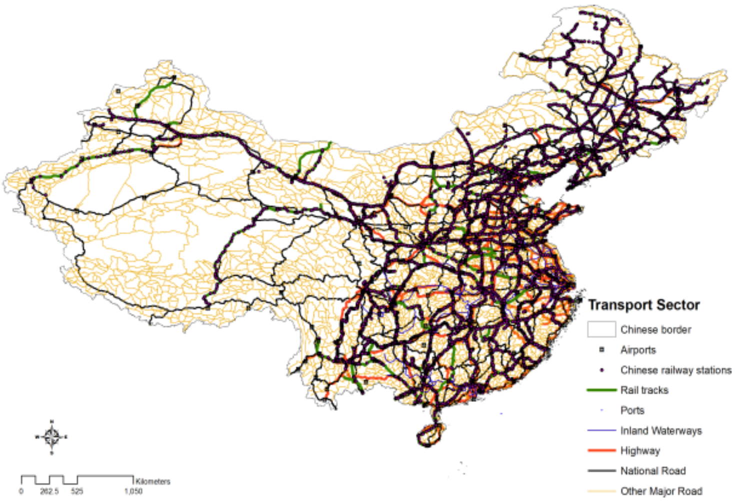


Figure 3. The Chinese Transport Network

Source: Harvard ChinaMap, Natural Earth, the World Port Index, the Chinese National Planning Commission, and the Second National Inland Waterways Census.

Figure 4 illustrates why China is vulnerable to flooding impacts in particular. Its river system is extremely extensive and dense; and we cover a total length of 1,109,635.9 km in our dataset. In order to control adequate water supply, the country has built 540 large reservoirs and 3,108 medium-sized reservoirs (Ministry of Water Resources 2011b). However, it would appear that on average the water supply is decreasing in China as the total water storage volume for these reservoirs now stands at 319.65 billion m^3, which compared with 2010 decreased by 169.1 billion m^3 (*Ibid*).

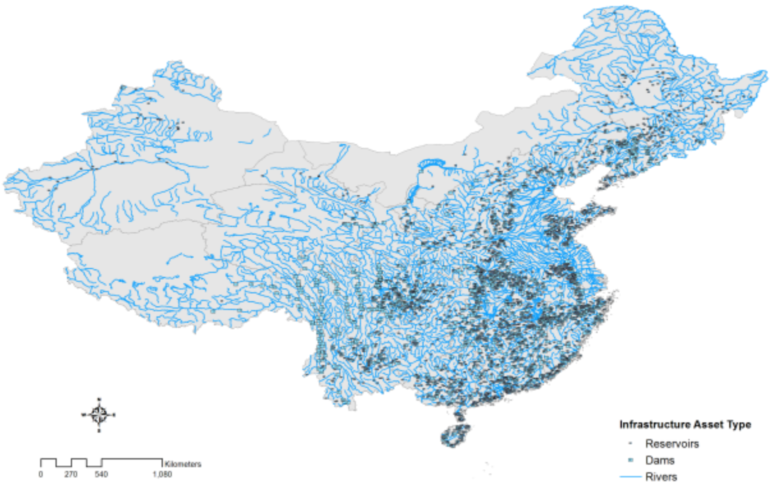


Figure 4. The Chinese Water Sector

Source: Chinese Ministry of Water Resources and Lehner *et al.,* 2008.

Figure 5 shows a comprehensive spatial distribution of the Chinese wastewater sector with a full dataset obtained from the Chinese Ministry of the Environment, and a partial picture (33.7% of the total) of the solid waste sector (Ministry of Housing and Urban-Rural Development 2013). Only a partial database of the solid waste sector can be constructed, as readily available data does not exist. Therefore we construct our own database by firstly identifying the 658 cities in China as defined by the central government and secondly searching on the web whether these cities have published data on their waste treatment plants.

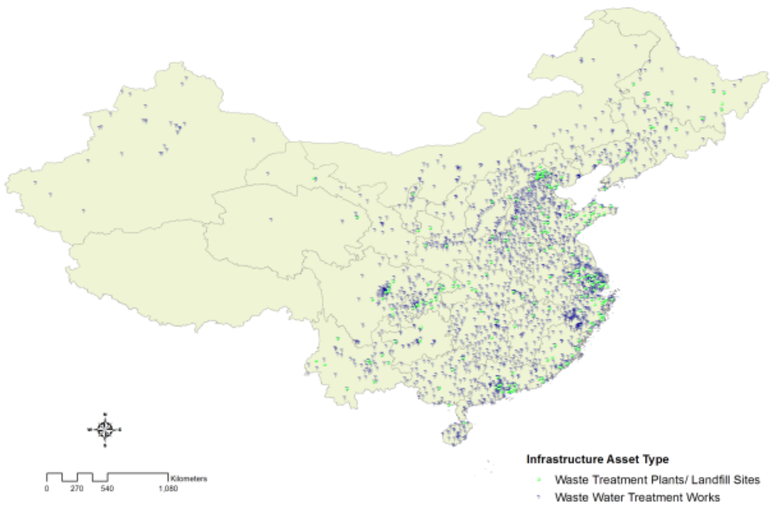


Figure 5. The Chinese Waste Sector

Source: Chinese Ministry of the Environment (2012)

There appear to be four vulnerable centers of waste plants clustering around the four major cities in China: Beijing, Shanghai, Shenzhen and Chongqing. Vulnerability of this sector may further increase as the government intends to spend RMB 1 trillion to improve water treatment and recycling facilities, including the construction of 800 to 900 new water processing and wastewater treatment plants (KPMG 2009).

Figure 6 gives a very limited understanding of the vulnerability of the ICT sector to flooding risks, as spatial data is restricted owing to its sensitivity. However, we know that the actual vulnerability is significant. By 2012, the national optical fiber cable network increased by 2,686,000 km, reaching a total length of 14.806 million km (Ministry of Industry and Information Technology 2013). Mobile telephone exchange capacity totaled 1,828,698,000 households and broadband access ports reached 268,355,000 (*Ibid*).

Figure 6. The Chinese ICT Sector

Source: the China Internet Data Centre (IDC) database.

4.3. Methodology

The aim of this paper is to demonstrate a methodology that provides insights into the locations of critical infrastructure at risk to flooding on a broad scale, and one that is capable of predicting the potential number of customers affected on the local scale should infrastructure assets fail owing to one or a series of flooding event(s). We do this by firstly allocating customers to each infrastructure asset at the local (plant) level for each sector – for example, water, energy, transport, waste and ICT – since the customers dependent on each infrastructure asset vary according to the type of infrastructure. Owing to data restrictions, we apply different methods for the transport and non-transport sectors. Upon customer allocation to assets, we apply a Kernel estimation to identify 'hotspots' of vulnerability and impose a flood frequency map to obtain an idea of critical infrastructure assets exposed to flooding risks at the broad scale.

4.3.1. Customer allocation for the transport sector

For the transport sector (e.g. airports, ports), we use passenger statistics to give an indication of the scale of interruption should infrastructure assets fail. For example, we collect data on the total number of passengers for airports (2012) and ports (2011). Regarding railway stations, it is not possible to obtain passenger flows for each station; we approximate the number of customers through each station by the way it is defined. The Ministry of Rail (now China Railway Corporation) classifies all railway stations into six categories, depending on the type of use (passenger, cargo, marshaling yard or a mixture), sizes of passenger flow, cargo volumes and its "strategic importance" (Ministry of Rail 1980). These include "special grade", "grade 1", "grade 2", "grade 3", "grade 4", and "grade 45". The stations are assigned the approximate number of passengers according to their categories (see Table 3).

Table 3. Railway stations classification and their associated daily passenger and cargo volumes

Railway station classification	Railway use (passenger, cargo, marshaling yard)	Average daily passenger flow	Average daily cargo volume (trucks)
Special	Single use	> 60000	> 750
	Multi-use	> 20000	> 450
1	Single use	> 15000	> 350
	Multi-use	> 8000	> 200
2	Single use	> 5000	> 200
	Multi-use	> 4000	> 100
3	Single use	N/a	N/a
	Multi-use	> 2000	> 50

Source: Ministry of Rail 1980

4.3.2. Customer allocation for the non-transport sector

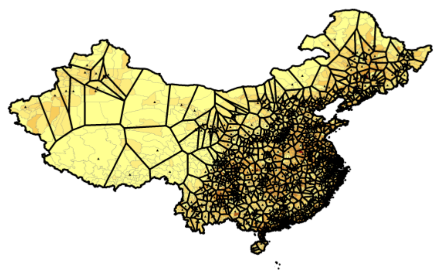
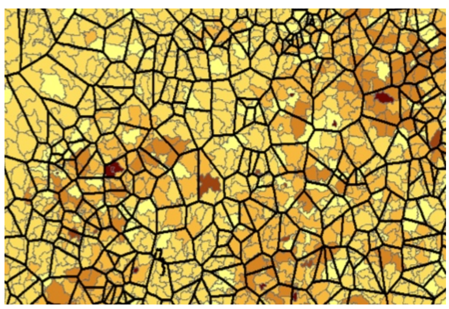
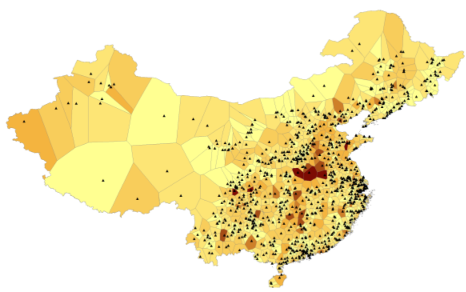
Our customer allocation method for the non-transport sector is adapted from the ITRC and we demonstrate the methodology with the Chinese electricity sub-sector. The allocation must satisfy two conditions:

a. The customers we allocate to each power plant must be closest to that plant than any other in the surrounding area.
b. The number of customers served by any power plant is proportional to its capacity. In other words, all power plants of the same capacity serve roughly the same number of customers.

Voronoi diagram for customer allocation

In order to satisfy the above conditions, we first create a Voronoi diagram for each asset (e.g. power stations) where a number of regions are set according to the asset locations. Each corresponding region consists of all points closer to one particular asset than to any other. Second, we intersect this layer of Voronoi diagram with the 2010 county-level population census data released by the Chinese Statistical Office. Third, we calculate the population density (α) for each county and multiple α with the intersected regions for each infrastructure asset (see Table 4). Thus, for each region the asset is located in, we have a preliminary customer footprint that is reliant on the infrastructure asset.

Table 4. Preliminary customer allocation by Voronoi diagram in GIS

Step 1: Build a Voronoi diagram (*Thiessen polygons in GIS*) with plant locations.	Step 2: Overlay the *Thiessen polygons* with county *population polygons*. Within each *population polygon*, we calculate the population density (α) by dividing the population with its area.
	
Step 3: Within each *Thiessen polygon*, there are typically many *population polygons* of different population densities. We calculate the areas of *population polygons* within the intersected *Thiessen polygon* in GIS.	Step 4: Transfer the demand from the *population polygons* to the *Thiessen polygons*. The total demand within each *Thiessen polygon* equals the areas of intersected *population polygons* x population density (α). Therefore we obtain the demand (i.e. population) for each Thiessen polygon that one infrastructure asset is based on.
	

Source: adapted from ET Geo Wizards, 2013

Optimizing the ratio between power plant capacity and its customers

Once we obtain a preliminary number of customers for each power plant, we need to further refine the analysis because in some cases, we have allocated too many customers to a power plant. In these instances, we must redistribute some of these customers who are furthest apart from the power plant, to another plant that is the next nearest and is supplying to less customers. In other cases, we do not have enough people in some power plants, we need to relocate some people from a nearby power plant that has too many customers and move them into those that do not have enough people. Thus we seek to optimize the allocation of n counties, $A_1,\ldots, A_n$, with populations $p_1,\ldots, p_n$, respectively, to m power plants, $P_1,\ldots, P_m$ with capacities $c_1,\ldots, c_m$, respectively, in a way that seeks to have roughly equal population per unit of capacity.

We define $d_{i.k}$ as the distance between county i and power plant k in order of distance $d_{i,a} < \ldots < d_{i,E}$, and we allocate counties $A_a,\ldots, A_z$ to power plant P_k, so P_k serves a population of $p_k = p_a + \ldots + p_z$. We seek to minimize the variance in the ratio c_k/p_k:

$$\min\left[\frac{1}{m}\sum_{k=1}^{m}\left(\frac{c_k}{p_k}-\mu\right)^2\right]$$

where $\mu = \sum_{k=1}^{m} c_k \,/\, \sum_{i=1}^{n} p_i$, whilst at the same time allocating counties to their nearest power plants. Our algorithm is as follows:

---

1. Find μ the mean ratio between power plant capacity and county population
2. For all power plants, P_k, that has a c_k/p_k ratio < μ (too many people):
   - 2.1. Find the furthest county, A_f, from P_k and its population p_f
   - 2.2. Find A_f's nearest plant P_j. If $c_j/p_j > c_k/p_k$ reallocate population p_f from P_k to P_j.
3. For all power plants, P_k, that has a c_k/p_k ratio > μ (not enough people):
   - 3.1. Find county, A_c, that is closest to P_k but is not one of the counties $A_a,\ldots, A_z$ already allocated to power plant P_k. Find A_c's population p_c.
   - 3.2. Suppose that A_c is currently allocated to P_j. If $c_j/p_j < c_k/p_k$ reallocate population p_c from P_j to P_k.

4. Confirm that this reduces $\frac{1}{m}\sum_{k=1}^{m}\left(\frac{c_k}{p_k}-\mu\right)^2$. It will by definition reduce $\frac{1}{m}\sum_{k=1}^{m}\sum_{i=a}^{z} d_{i,k}$.

Hot-spot analysis using Kernel density estimation

Following customer allocation for each infrastructure asset that satisfies the two conditions set out in earlier, we then use a kernel density estimator (KDE) to convert the discrete spatial measures of customer demand to a spatially continuous surface of demand. A 0.15 km spatial lattice is constructed across China and it contains individual infrastructure assets at which KDE was performed. The output units are density per km^2. The KDE is defined as:

$$g(x_i) = \sum_{j=1}^{n}\left\{[P_j]\frac{1}{\pi h^2}K\left(\frac{e_{ij}}{h}\right)\right\}$$

where $g(x_i)$ is the density at lattice location x_i, P_j is the customer demand associated with asset j, h is the bandwidth of the density estimation (search radius) and $K\left(\frac{e_{ij}}{h}\right)$ is the kernel applied to point i that employs the distance e_{ij} $\forall\, j \;\leq h$. The kernel function employed in this study was a Gaussian:

$$K\left(\frac{e_{ij}}{h}\right) = \left\{\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{e_{ij}^2}{2h^2}\right)\right\}$$

Therefore, for the electricity and rail subsectors, we derive KDE surfaces both in terms of spatial frequency of infrastructure assets i.e. without associating customer demand and also in terms of customer demand. This process identifies the hotspots of vulnerability in terms of the potential number and locations of customers dependent upon an asset. Next, we classify 5 categories of hot spots (Jenks Natural Breaks Classification in GIS) and locate the number of customers within the top two categories as concentrations of exceptional vulnerability.

Impose flooding frequency map on the hot-spot analysis

Lastly, we impose a flooding frequency map based on historical records at city-level (1985-2011, Dartmouth Observatory) onto our hot-spot analyses. This provides us with a spatial understanding of how infrastructure hotpots i.e. where customers are concentrated might be vulnerable to flooding impacts.

4.4. Results and Discussion

We apply our methodology to the rail and electricity subsectors. For the rail subsector (Figure 7), we identify some stations in the southwest that are exposed to high levels of flooding risks. The concentration of customers (1,779,000) in the northeast where hotspots are identified, is not located in cities where flood frequency is the highest.

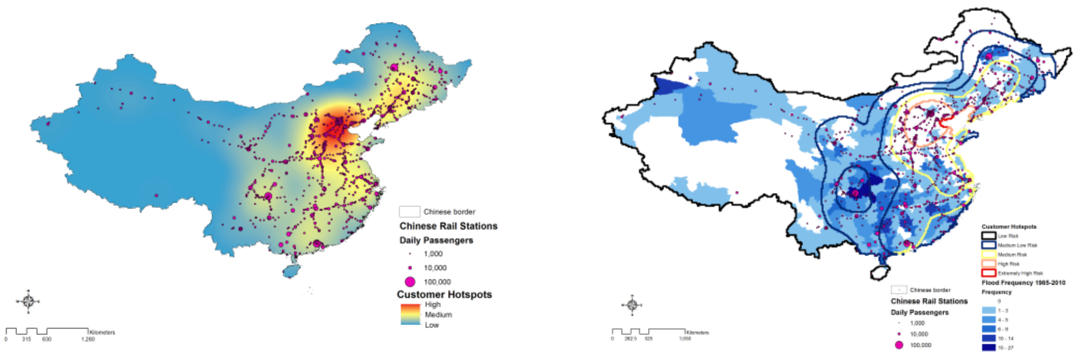


Figure 7. Left: Rail Stations Customer Hot-Spot Analysis at 5km Search Radius. Right: Rail Stations Customer Hot-Spots at 5km Search Radius Imposed with Flooding Frequency Map at City-level 1985-2010.

The same story applies to the electricity subsector (Figure 8), customer hotspots (a total of 424,964,097) are concentrated around Beijing, Shanghai, and Shenzhen. Their exposure to high flood risk in terms of frequency of past flooding events (1985-2010) is relatively low as well because they tend to be situated in cities where flooding frequency is in lower categories.

Electricity sub-sector

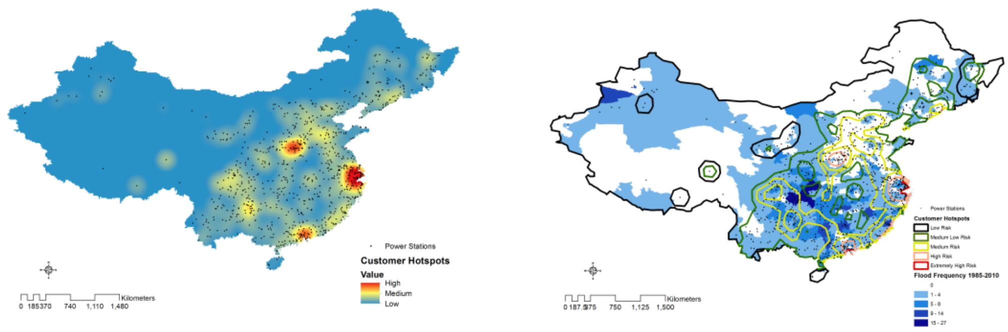


Figure 8. Left: Power Stations Customer Hot-Spot Analysis at 2km Search Radius. Right: Power Stations Customer Hot-Spots at 2km Search Radius Imposed with Flooding Frequency Map at City-level 1985-2010.

4.5. Conclusions

It is recognized that economic vulnerability to flooding, both at present and in future climates, is a huge challenge in China. Impact and risk assessments have tended to focus upon the people and assets that are directly located in floodplains. In this paper we have taken a first step to understanding the potential for indirect damage and disruption, by estimating the numbers of people indirectly dependent on infrastructure assets and pinpointing locations where critical assets are concentrated in floodplains. The overall results show that infrastructure hotspots do not seem to be located in high flooding risk areas for now. Future work will extend the 'criticality hotspots' analysis to all other subsectors in Table 2 and study the network effects influence the propagation of infrastructure failure when flood hazards materialize.

5. The Spatial Exposure of the Chinese Infrastructure System to Flooding and Drought Hazards

5.1. Introduction

China has overtaken the United States and the EU to become the world's largest investor in infrastructure (Dobbs et al. 2013). The country has invested 8.5% of its GDP into its infrastructure since 1992 and its stock of infrastructure as a percentage of GDP is now, at 71%, above the global average (*Ibid*). Whilst ambitious plans are in place to increase this stock even further, concerns have been raised over the extent to which its infrastructure system can withstand natural disasters such as flooding and drought. According to the Chinese Ministry of Water Resources, the 2011 floods alone resulted in the interruption of services to 28 rail links, 21,961 roads and 49 airports, and the failure of 8,516 electricity transmission lines (Ministry of Water Resources 2011a). The 2012 droughts affected a substantial proportion of the Chinese water supply – thousands of reservoirs issued warnings of "exceptional low water levels" in provinces such as Hubei, Yunnan and Heilongjiang, resulting in water shortage in urban areas (Ministry of Water Resources 2012). Meanwhile, the 2011 drought caused the water level at the world's biggest hydropower plant – the Three Gorges Dam – to fall to 152.7 metres, well below the 156m mark required to run its 26 turbines effectively (Stanway 2011).

This paper seeks to understand how the Chinese infrastructure system is exposed to flooding and drought impacts. We do this by taking a first step to explore the potential of disruption to infrastructure systems and the people and industries that they serve (infrastructure 'users') caused by these events. Instead of conventional impact and risk assessments that tend to focus on the people and assets directly located in floodplains and drought-prone areas, we estimate the numbers of people dependent on infrastructure assets ('users') and pinpoint locations where critical assets are concentrated in these high-risk areas. As a result, we show the locations of critical infrastructure that are exposed to risks of flooding and drought on a broad scale – and calculate the potential number of users affected should infrastructure assets fail owing to one or a series of flooding/drought event(s) on a local scale.

The outline of the paper is organised as follows. Section 5.2 presents a general literature review around exposure/vulnerability analysis, infrastructure network exposure/vulnerability and an introduction to the Chinese context. Section 5.3 describes the methodology we adopt and the data sources. Section 5.4 presents our results, and Section 5.5 discusses the assumptions, the validity of our results and the policy implications. Section 5.6 concludes.

5.2. Literature Review

Literature on exposure to natural hazards is often discussed in the context of natural disaster risk reduction. The IPCC SREX (Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation) report defines risk to natural disaster as a function of *hazard*, *exposure* and *vulnerability* (IPCC 2012a). *Hazard* refers to the "possible, future occurrence of natural or human-induced physical events that may have adverse effects on vulnerable and exposed elements"; *exposure* refers to the "inventory of elements in an area in which hazard events may occur"; *vulnerability* refers to the "propensity of exposed elements such as human beings, their livelihoods, and assets to suffer adverse effects when impacted by hazard events" (*Ibid*).

Risk-based studies are ideal because they are probabilistic assessments of possible future hazard events and their impacts (Li et al. 2012; Wu et al. 2012). Unfortunately, much of the literature has not been able to determine the probability quantitatively owing to the huge uncertainties involved and a lack of data. As such, most relevant literature for our study is in exposure and vulnerability. Given that exposure studies are usually part of broader vulnerability analyses, we review scholarly work under the general heading of "vulnerability analysis".

5.2.1. Vulnerability analysis

In the context of vulnerability to flooding and drought impacts, one may summarise three main approaches used. These are: qualitative, potential consequences and impact assessment. Qualitative approaches are the first generation of vulnerability studies. These are often derived from surveys and interviews, which are sufficient for obtaining a general idea of the possible vulnerabilities to flooding and drought and particularly useful for understanding the decision-making process (De Sherbinin et al. 2007; Regmi & Hanaoka 2011; Zarafshani et al. 2012). However, they remain largely descriptive and hard to compare across systems.

Potential consequences approaches assess the vulnerability of a system to flooding and drought impacts by looking at how the system may be affected if hazards occur (HSBC 2011; IPCC 2012a; Wilhelmi & Wilhite 2002; Lewis 2009; Dutta et al. 2003). On the other hand, impact assessments approaches examine how a system has been affected by past flooding and drought events, in contrast to potential consequences approaches where vulnerabilities are based on how a system may cope given the possibility of future flooding/droughts, often measured by population or economic impacts (World Bank 2004).

5.2.2. Infrastructure network vulnerability

Recently, vulnerability studies of the infrastructure systems and networks have sprung up owing to concerns over increasing levels of “threats”, which may or may not originate from natural disasters such as flooding and drought (Mao et al. 2009; Erath et al. 2009; Marrone et al. 2013). Here we first discuss some general methods for understanding infrastructure network vulnerability, and then examine approaches taken in the context of flooding and drought disasters.

Traditionally, scholars have sought to address network vulnerability with graph/network theories. This involved using network measures focused on the centrality of a vertex in the graph, including degree centrality, betweenness, closeness, and eigenvector centrality (Dinh & Xuan 2012). While these metrics do provide some insights into network vulnerability, they typically fail to reveal the level of network disruption for different levels of attacks (*Ibid*). Therefore global graph measures such as the number of vertices and edges have been introduced to study network connectivity performance under different attack strategies (Holme et al. 2002). Applications of such theories can be found in the Information & Communication Technology (ICT) and the power sectors where fictional or real networks are studied (Baiardi & Corò 2013; Bompard et al. 2013; Mao et al. 2009; Matisziw et al. 2009).

Although graph/network theories reveal vulnerable system property or vulnerable system components of an infrastructure network, they do not typically incorporate the functional aspects of the components in the network, for example power flows in the electricity sector (Dueñas-Osorio & Vemuru 2009; Johansson & Hassel 2010). Indeed, some scholars are in favour of using functional models and conclude that evaluating vulnerability in power networks using purely topological metrics can be misleading (Hines et al. 2010). Similarly, LaRocca and others conclude that in general, the greater the inclusion of functional characteristics, the better the estimate of the system's actual performance for a given failure scenario (LaRocca et al. 2012). However, owing to computational limitations, it is not always possible to include these functional characteristics (*Ibid*).

It is more often the case however, that network and functional models are used in conjunction with each other when analysing the vulnerability in interdependent networks and cascading effects (Johansson & Hassel 2010; Bompard et al. 2013; Shuang et al. 2014; Wang et al. 2013). Depending on the time frame, Ouyang and colleagues argue that network models are helpful to design or improve the infrastructures in the long run while focusing on functional vulnerability is useful to protect them in the short term (Ouyang et al. 2009).

Unfortunately, studies that are specifically concerned with infrastructure network vulnerability due to flooding and drought disasters are rare in the literature. Most of them reside within the "potential consequences" domains as discussed in Section 5.2.1 and work with urban or regional scales (Tang et al. 2013; Oswald & Treat 2013).

Infrastructure network vulnerability in China

As a result of the phenomenal growth of Chinese infrastructure over the past few decades, its networks are now among the world's largest. For instance, the country's expressway network, which is already the second largest in the world, has been growing at an average of 20 per cent per year since 2000 (KPMG 2008; KPMG 2009). China's railway system – the world's third largest network – has 6 per cent of the world's track length (and rising) and carries 25 per cent of the world's traffic (*Ibid*). China's inland waterway transport (IWT) network is the world's largest, and the country surpassed the U.S. as the world's largest Municipal Solid Waste (MSW) generator in 2004 (World Bank 2007; World Bank 2005).

Given the scale and speed at which Chinese infrastructure networks have grown, one may postulate that these networks might be more susceptive to different threats. Some recent studies have looked at the vulnerability of Chinese infrastructure from a network perspective. For instance, applying a network model to the power and gas pipeline systems in a non-specified Chinese city, Wang and colleagues analyse interdependent responses under three types of edge disturbance strategies and propose a method for ranking critical components (Wang et al. 2013). Taking the Chinese railway system as an example, Ouyang and others select three typical complex network-based models to analyse railway accessibility and flow-based vulnerability (Ouyang et al. 2014). Using the power network of a major city in Central China as a case study, Mao and others show that the network exhibits small-world network properties and demonstrate the vulnerability of the network under selective attacks and random failures (Mao et al. 2009). Taking the power and water systems of a major city in China as an example, Wang and colleagues develop a framework for analysing the vulnerability of interdependent infrastructure systems (Wang et al., 2012).

Literature concerned with infrastructure vulnerability due to flooding and drought impacts in China – most of which reside in the "potential consequences" domain as discussed in section 5.2.1 – is yet scarcer. Xie and colleagues present a framework of reliability analysis, based on fragility curves, of the dike system for the Taihu Basin in China (Xie et al. 2013). HSBC overlay the locations of planned power stations with water scarcity maps, showing the vulnerability of power sector (HSBC 2012). Our work contributes to the current literature by building an infrastructure exposure map of China across multiple sectors and locations for the first time. In addition, this particular exposure study not only provides an inventory of infrastructure assets, but also seeks to quantify the potential scale of disruption due to infrastructure failure. We do this by developing a new metric of estimating the number of exposed populations who might be vulnerable to natural hazards because they are either directly or indirectly dependent on the infrastructure assets concerned. Therefore, the work presented here is a first study that has demonstrated the exposure of Chinese infrastructure to potential direct/indirect natural hazard impacts.

5.3. Methodology

Flooding and drought events might affect the infrastructure system in significant ways. Examples of flooding impacts on the infrastructure include: water-induced asset damages and temporary inaccessibility to sites such as roads. Similarly, drought could result in water levels being severely lowered in hydropower reservoirs and reduce the amount of cooling water for electric power generation. In this paper, we seek to provide insights into the locations of critical infrastructure exposed to flooding and drought impacts on a broad scale, and estimate the potential number of users affected on the local scale should infrastructure assets fail owing to one or a series of flooding/drought event(s). This method builds a common metric i.e. the number of users that allows the impacts of flooding/drought to be compared across sectors, even though the nature of these disruptions varies.

First, we introduce the general framework for understanding the infrastructure system (Figure 9), whereby infrastructure sectors and assets are specified and relevant data are collected. Second, we allocate users to each infrastructure asset at the local (asset) level for each sector since the users' dependence on each infrastructure asset varies according to the type of infrastructure. Upon user allocation to assets, we apply a Kernel density estimation to identify 'hotspots' of exposure. Fourth, flood and drought maps are overlaid onto the infrastructure "hotspot" analyses in order to obtain an idea of critical infrastructure assets exposed to flooding/drought on the broad scale. The output of the paper translates to infrastructure hotspot maps integrated with flooding/drought hazards and the number of users as a common metric to measure exposure.

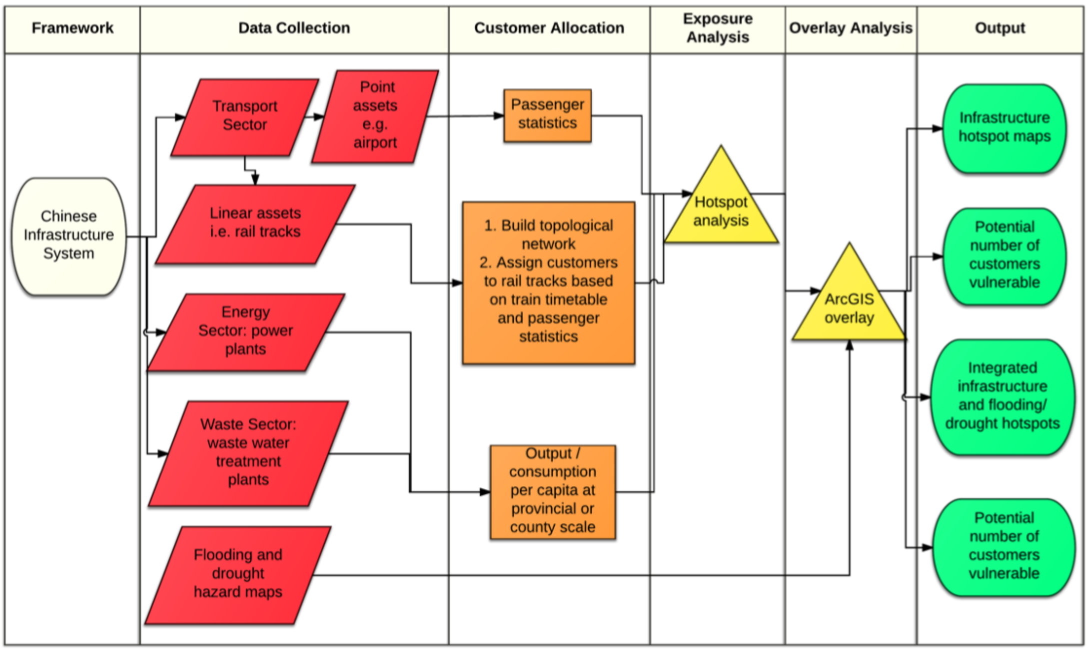


Figure 9. Overview of methodology

5.3.1. Framework for understanding the Chinese infrastructure system

We define the infrastructure system as an integrated system consisting of five sectors – energy, transport, water, waste and ICT (Hall et al. 2014). Within each of these sectors, component systems are identified and we construct an infrastructure database according to the framework shown in Table 5.

Table 5. Summary of the Chinese National Infrastructure System

Sector	Sub-sector	Asset type	Number of Assets	Source	Completeness (%)
Energy	Electricity	Power plants	2116	Enipedia	67
Transport	Rail	Rail tracks	2863	OpenStreetMap	100
		Stations	5401	Harvard WorldMap Project	100[1]
	Aviation	Airports	146	Civil Aviation Administration of China	80
	Shipping	Ports	155	China Ports Yearbook	3
Waste	Waste water	Waste water treatment works	2743	Chinese Ministry of the Environment	100

Source: adapted from Hu et al. (2014)

[1] Note no officially disclosed data exist for the total number of train stations in China. The 100% comes from personal communication with China Rail Administration (CRA). In 2010, the total number of train stations was at 5,287. Our database with 5,401 exceeds the number provided by the CRA, thus we assume it is reasonably complete.

Data on the electricity sub-sector

We focus our energy work on the electricity sub-sector and obtain a total of 2,218 nodes which represent power plants from Enipedia (Davis et al. 2014). Although Enipedia contains the best open source spatial dataset that the authors are aware of, it is not complete. In Figure 10. Data completeness (in percentage) from Enipedia's database per province in China., we show the data completeness (in percentage) from the Enipedia database for individual provinces by aggregating the total amount of annual output produced by all power plants within each province and comparing that with official statistics on the annual electricity consumption for that province from the China Electric Yearbook (China Electric Power Yearbook Editorial Committee 2011). Information on provincial annual electricity consumption from the China Electric Power Yearbook is digitised and translated; no data are available for individual power plants nor their spatial locations hence we use Enipedia and only verify the data with the China Electric Yearbook. We find that data are better represented in north-eastern China; Tibet, Shaanxi and Ningxia provinces have the most incomplete datasets[2].

[2] Note that Hunan province has a percentage at 101% and Jilin province at 109%, which may be a reflection of data inaccuracy of the Enipedia database. In this case, Enipedia has collected power plant data, which exceed the official database's output. Data on Taiwan, Hongkong and Macao do not exist hence exhibit 0%.

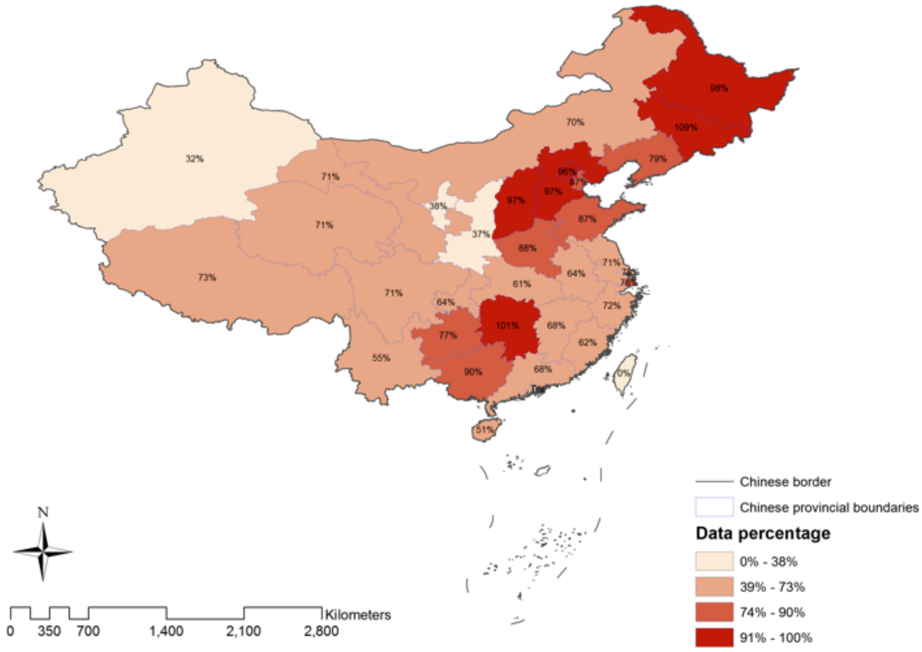


Figure 10. Data completeness (in percentage) from Enipedia's database per province in China.

Data on the transport sector

The total lengths for the rail network that we generate with our model (for details, please refer to "Transport sector: linear assets" in Section 5.3.2) in our dataset cover 138,414 km and we verify this with OpenStreetMap (OpenStreetMap Contributors 2014). We assume that this coverage is 100% as the Ministry of Rail reports that the total operating length of the Chinese rail network extends to 98,000 km (Ministry of Rail 2012). For train stations, we download data from the Harvard China Map which contains 5401 train stations (The Harvard WorldMap Project 2014). For aviation, we obtain and translate the list of currently operational airports (183 Chinese civil airports) and those that are being planned to 2020 from the Civil Aviation Administration of China (Civil Aviation Administration of China 2008; Civil Aviation Administration of China 2013). This list is translated into English and 146 currently operational airports are geocoded in Google Earth. In addition, we collect data on the total number of passengers for airports, for the year 2012, and ports, for the year 2011 (Civil Aviation Administration of China 2013; China Academy of Transportation Sciences 2005). A VBA code is developed to match passenger data with the airports in the list from the Civil Aviation Administration of China. Finally, passenger data on ports come from the China Ports Yearbook and are geocoded in Google Map (Editorial Board of China Ports Yearbook 2012).

Data on the wastewater sub-sector

A full dataset for wastewater treatment works (2,743 assets) is obtained from the Chinese Ministry of the Environment (Ministry of the Environment 2013). The dataset contains full name of the treatment plant, daily capacity and city information. As we do not know the exact location for each plant, we resort to a thorough process of searching plant addresses online and geocoding these in Google Earth and/or Baidu to our database.

Data on population and administrative regions

Population data are obtained from the "Tabulation on the 2010 population census of the people's republic of china by county" released by the Chinese Census Office (Chinese Census Office of the State Council 2012). This is one of the most recent and comprehensive datasets covering population data for China's 2,872 counties (*Ibid*). For each province, city, county, village and hamlets, there are detailed data on the number of residents, households and so on. We amalgamate population data with the administrative boundary data provided by Beijing Normal University in the Atlas of Natural Disasters in China (Shi 2011).

5.3.2. User allocation

Transport sector – point assets

We allocate users to point assets such as airports, train stations and ports using passenger statistics based on data collected in section 5.3.1. As data on passenger flows for train stations do not exist, we develop a simple methodology that approximates the number of users through each station by the way it is defined (see Table 6). The Ministry of Rail (now the China Railway Corporation) classifies all railway stations into six categories, depending on the type of use (passenger, cargo, marshalling yard or a mixture), sizes of passenger flow, cargo volumes and "strategic importance" (Ministry of Rail 1980). Each station is assigned a daily passenger number using the minimum threshold given in Table 6 as a proxy. For instance, a single-use special graded station will have an average daily passenger flow of 60,000 whereas a multi-use station will have 20,000.

Table 6. Railway stations classification and their associated daily passenger and cargo volumes

Railway station classification	**Railway use (passenger, cargo, yard)**	**Average daily passenger flow**	**Average daily cargo volume (trucks)**
Special	Single use	> 60000	> 750
	Multi-use	> 20000	> 450
1	Single use	> 15000	> 350
	Multi-use	> 8000	> 200
2	Single use	> 5000	> 200
	Multi-use	> 4000	> 100
3	Single use	n/a	n/a
	Multi-use	> 2000	> 50

Source: Ministry of Rail 1980

Transport sector – linear assets

Assigning users to linear assets such as rail tracks is not straightforward, as readily available data do not exist. In this paper, we demonstrate an approach allocating users to the Chinese rail sub-sector in accordance with data from train timetables. First, we collect a comprehensive dataset of the 4060 Chinese "rail routes", which represent all passenger rail "traffic" in China between one and three days (Ministry of Rail 2010). Second, we build an approximate railway topology network by assigning a straight line between every pair of stations for each "route". Overlapping stations are removed. This way, one line (i.e. track) is assigned between any two stations (Figure 11). Artificial straight lines are used because we have incomplete data on the rail network. Third, we verify this network dataset with the 2014 rail track dataset from OpenStreetMap[3] (shown in Figure 12). Lines shorter than 200 kilometres are well represented because they are located in densely urbanised areas, therefore tend to be straight and are short in length. We replace lines that are more than 200 kilometres in length with the actual track alignment because they do not align well with the real tracks after verification.

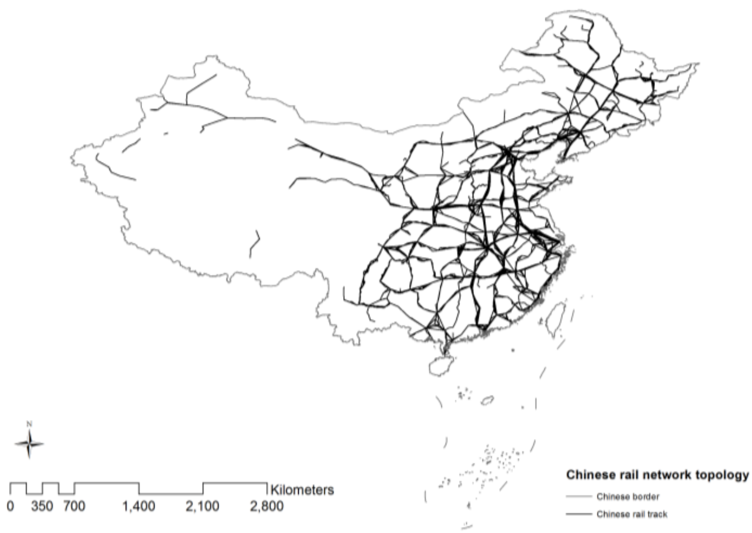


Figure 11. The Chinese railway topological network created by assigning a straight line between every pair of stations for each "route"[4].

[3] The OpenStreetMap dataset has rail tracks and station data in separate files. This means that some stations are off the track where others have no tracks nearby. Since our "rail routes" data are stored in station-to-station format, we resort to constructing our own tracks and verify these with the OpenStreetMap tracks.

[4] All results in this paper do not include Taiwan, Hongkong and Macao, as data do not exist for these regions.

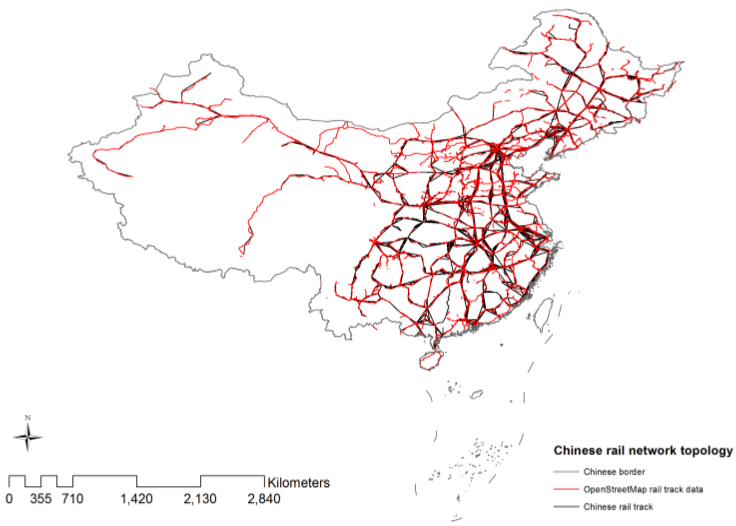


Figure 12. Verification of artificially built topological Chinese rail network with the 2014 OpenStreetMap datasets.

Once we build the railway topological network, we assign passenger numbers over track paths. For each route, we record the stations it passes, for example, route “1” goes through stations A – B – F – E – D and route “2” goes through stations A – B – C – D (see Figure 13). We also note the number of passengers the train carries. For instance, Electric Multiple Units (EMUs) often take 915 passengers (please refer to Appendix 1 for a full list of carrying capacity for different types of train). Given that the carrying capacity is similar for all types of trains, we restrict our analysis to using the average passengers per route i.e. 1062 for allocating users to rail tracks. Assuming the trains are operating at full capacity, we aggregate the total flow of passengers through each track between any two stations during a three day period: in Figure 13, the total number of passengers for the track between stations A and B is 116 + 118 = 234.

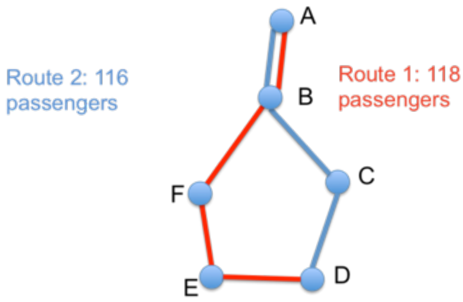


Figure 13. Calculation of total passengers through track A – B during any three-day period.

Building the topological railway network based on national train timetables provides us with information on the train frequency on each track. With supplementary data on the passenger capacity of each train, we are able to assign a total number of daily users to each track.

Electricity sub-sector

For the electricity sub-sector, we allocate users to each plant based on data on actual output per plant and electricity consumption per capita for the particular province in which the plant is located. The number of users per power plant, C_p, is given by the equation:

$$C_p = P_a * \frac{E_{p,a}}{D_a}$$

where $E_{p,a}$ is the energy output in megawatt-hours per year for power plant p in a particular province a; D_a is the electricity consumption (in megawatt per hour) of province a; and P_a is the population of province a.

We also consider the possible number of users missing from the analysis for each province. We do this by adding the total number of users, $C_{p,a}$, allocated for all power plants within province a and comparing $C_{p,a}$ with the aggregate population for province a. The aggregate number of users missing, M_a, for province a is given by the equation:

$$M_a = P_a - \sum_{i=1}^{p} C_{p,a}$$

In reality, the number of users missing in provinces will vary enormously depending on the output capacity of the province. In fact, the aggregate number of users for some provinces should exceed the total population whereas for other provinces, it should fall below the population. This is owing to the fact that some provinces are "surplus" producing states that produce more electricity than they consume, whereas others are "deficit" states that produce less electricity than they consume. Figure 14 depicts these "surplus" and "deficit" provinces in blue and red respectively; we may assume that electricity is flowing from the blue provinces to the red through high voltage transmission lines.

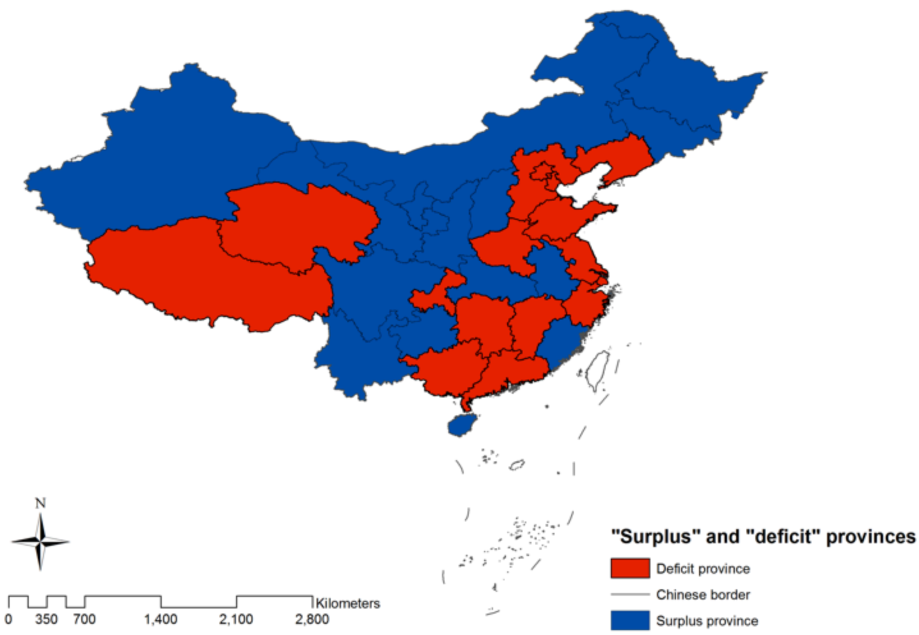


Figure 14. Electricity production and consumption "surplus" and "deficit" province comparisons. Provinces in "blue" are those that produce more than they consume whereas "red" provinces consume more than they produce.

Source: China Electricity Yearbook 2012

Wastewater sub-sector

For the wastewater sub-sector, we take a similar approach with user allocation as we did to the electricity sub-sector except for the scale, which is at county-level. In some cases, we remove some of the wastewater treatment plants from our full database as we do not have data on volume treated; in other cases, many plants have not been operationalised. Our analysis is based on a reduced sample of 1,680 plants as opposed to the full database of 2,743. We define the number of users, C_w, per waste treatment plant as:

$$C_w = P_b * \frac{V_{w,b}}{V_b}$$

where $V_{w,b}$ is the daily volume treated in 10,000 m^3 for waste treatment plant w in county b; V_b is the total waste water treated for county b; and P_b is the population of county b. V_b is calculated by equation (1) as shown below, where we aggregate all the waste water treated in any county b:

$$V_b = \sum_{k=1}^{w} V_{w,b} \tag{1}$$

5.3.3. Exposure and hotspot analysis

Since the aim of the paper is to provide insights into the locations of critical infrastructure at risk to flooding and drought impacts both on a broad and local scale, we need to translate the exposure of those users who have only been allocated on a local level to an exposure understanding on a broad level. The concept of "hotspots" is particularly useful because it provides a visual representation of exposure aided by a geo-spatial representation of "priority areas" for planners to focus on.

We apply the Kernel density estimator (KDE) to derive "hotspots" for the locations of critical infrastructure assets and networks. A KDE is a non-parametric statistical method for estimating the density of data. Here we apply the KDE spatially, using the number of users dependent on an asset as our data. This way, a spatially continuous surface is constructed. The KDE is formally defined as:

$$g(x_i) = \sum_{j=1}^{n} \left\{ [P_j] \frac{1}{\pi h^2} K\left(\frac{e_{ij}}{h}\right) \right\}$$

where $g(x_i)$ is the density at lattice location x_i (individual cells), P_j is the user demand associated with asset j, h is the bandwidth of the density estimation (search radius) and $K\left(\frac{e_{ij}}{h}\right)$ is the kernel applied to point i that employs the distance $e_{ij}\ \forall\, j\ \leq h$. The kernel function employed in this study was a Gaussian:

$$K\left(\frac{e_{ij}}{h}\right) = \left\{ \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{e_{ij}^2}{2h^2}\right) \right\}$$

Applying the KDE in China

For all Chinese infrastructure sub-sectors, we construct the same size spatial lattice, which contains individual infrastructure assets at which KDE is performed. The size of each cell within the lattice is set as the default value, which is based on the extent of the chosen spatial reference and is calculated as the shorter of the width or height of the output extent in the output spatial reference, divided by 250. This is based on an optimisation model within ArcGIS given the size of the lattices. Our chosen spatial reference is the “Asian_North_Albers_Equal_Area_Conic” in GIS and we transform it to the “GCS_China_Geodetic_Coordinate_System_2000” geographical coordinate system to minimise distortion. In addition, we use the same search radius (200,000 km) for all the infrastructure sub-sectors to obtain a consistent comparison among different hotspots. We conduct sensitivity analysis and find that the search radius 200,000 km provides the clearest visualisation of the results.

Disruption calculations

For all assets except rail tracks, our hotspot analysis is based on the number of users allocated to each asset. To calculate the potential disruption should assets fail after flooding/drought event(s), we classify five categories of hotspots (Jenks Natural Breaks Classification in GIS) and locate the number of users within the top two categories as concentrations of exceptional vulnerability.

With regard to the tracks for the rail sub-sector, our hotspot analysis is not solely based on users allocated to the tracks. Rather, it is based on the total potential disruption for each track, D_t. For any three-day period, we calculate D_t by multiplying train frequency for each track, f_t, with the number of passengers for each track P_t. f_t is the number of routes (i.e. train frequency) that each path track takes, for example, the f_t for track A – B is two in Figure 13. Formally, D_t is defined as:

$$D_t = \sum f_t \times P_t$$

Once users have been allocated, we standardise the time-scale so that users are allocated to all infrastructure assets on a yearly basis. For instance, the daily passenger freight for all rail stations is 1,205,000; therefore the yearly users at risk are 1,205,000 * 365 days in a year: 439,825,000. The three-day passenger freight for rail tracks is 913,320; thus the number of yearly passengers at risk is 913,320 * (365/3): 111,120,600.

5.3.4. Impose flood/drought hazard maps on the hot-spot analysis

Lastly, we impose flood/drought hazard maps from the CaMa-Flood model and the Atlas of Natural Disaster Risk of China onto our hotspot analyses (Yamazaki et al. 2011; Shi 2011; Fang 2011). This provides us with a spatial understanding of how infrastructure hotspots, i.e. where users are concentrated, might be exposed to flooding and drought impacts.

Method for assessing the flood hazard and risk

Flood risk is commonly defined as the product of the probability of flooding and the consequential damage, summed over all possible flood events (Hall et al. 2005). The probability of flooding for a national-scale flooding risk map is typically derived from some hydrological modelling based on meteorological data or simulation, analyses of extreme value statistics that estimate the severity floods at different return periods, and inundation modelling that estimates flooding depths for a given geographical unit (Ward et al. 2013). The consequential damage is conventionally evaluated by some economic impact modelling, for instance, by adopting indicators that show affected population, GDP, and/or exposed urban asset values (*Ibid*).

In this study, we make use of a global river routing model called the Catchment-Based Macro-scale Floodplain (CaMa-Flood) model to prepare the flood hazard map (Yamazaki et al. 2011). Briefly, the CaMa-Flood routes the runoff input simulated by a land surface model into the oceans or lakes along a prescribed river network. It calculates river channel storage, floodplain storage, river discharge, river water depth and inundated area for each grid-cell at a spatial resolution of 0.25° x 0.25°. A recently developed Global Width Database for Large Rivers (GWD-LR) is also incorporated into it (Yamazaki et al. 2014). Following Hirabayashi and colleagues, we drive the CaMa-Flood model using the daily runoff (1979-2010) generated by the Minimal Advanced Treatment of a Land Surface Interaction Runoff (MATSIRO) (Hirabayashi et al. 2013; Takata et al. 2003). We note that the MATSIRO model was forced by observations and reanalysis climate data (Kim et al. 2009).

Detailed description with reasoning and technical aspect of flood inundation map preparation using the CaMa-Flood model will be available in an upcoming paper on flood defence benefit and risk at the global scale (Lim et al.; in preparation). Here, we briefly describe the overall process of obtaining our flood inundation map. To prepare a flood inundation map of a specific magnitude, we select the Gumbel distribution (Gumbel, 1941) for its simplicity and demonstrated consistency with general extreme value statistics

(Dankers & Feyen 2008). We use annual maxima of river water depth (from CaMa-Flood) to perform extreme value estimation at each grid-cell. Based on the digital elevation models (SRTM3 DEM between 60° N and 60° S; GTOPO30 above 60° N (Hirabayashi et al 2013), we downscale and prepare the flood inundation map for a return period of 100 years at high spatial resolution (2.5' x 2.5') to support the analysis of this manuscript. This inundation map is used as the base flood hazard map and is further downscaled for the infrastructure hotspot analysis later.

Method for assessing drought hazard in China

Drought is the result of many composite factors such as high temperatures, high winds, low relative humidity, timing and characteristics of rain (Mishra & Singh 2010). Capturing drought risk of a probabilistic nature is difficult because of these complex factors involved; therefore several indices have been developed that characterise different aspects of drought risks. Prominent examples of drought indices include the Standardised Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Crop Moisture Index, the Surface Water Supply Index, the Vegetation Condition Index, and the Standardised Runoff Index (*Ibid*). Some indices, such as the SPI, only focus on precipitation, whereas others such as PDSI may incorporate variation in temperature, soil moisture, reservoir storage, streamflow, and snow pack (*Ibid*).

The assessment of drought hazard in China in this paper, R_L, is based on the anomaly percentage of precipitation, H_s, and the ranking of the sensitivity of land use, V_s, towards H_s in a 1-km grid (Shi, 2011). The equation is shown below:

$$R_L = H_S \times V_S$$

H_s is calculated as follows.

$$H_s = \frac{|Pa| - Pa\,min}{Pa\max - Pa\,min} \times 100\%$$

where $Pa = \frac{P - \bar{P}}{\bar{P}} \times 100\%$. P is the precipitation volume in any particular time period. $\bar{P}$ is the average precipitation volume in the time period concerned.

Six types of land use are considered, namely: arable land, grassland, woodland, urban, water areas, and unused land. Larger values of H_s indicate higher sensitivity of land[5] (Shi 2011). It is important to note that this drought assessment is hydrological in the sense that we identify high-risk areas when there is water deficiency. However, the way in which water infrastructure is affected by and/or influences water scarcity is not captured. Validation of the drought hazard map is shown in Appendix 5.

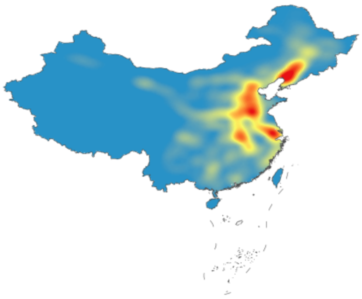
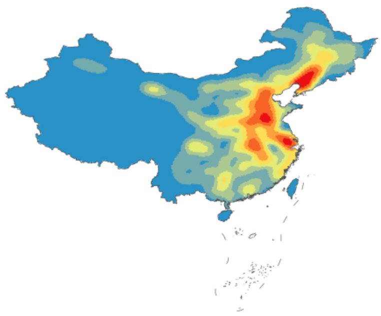
Integrating flooding and drought hazard maps with infrastructure hotspot analyses

In order to derive an aggregate understanding of how infrastructure hotspots are subject to flooding and drought impacts, we impose our hotspot analyses onto the flooding and drought hazard maps separately. For flooding, we look at all infrastructure sub-sectors. However, we restrict our study to the electricity sub-sector only for drought because, compared to electricity where a lack of water supply may result in suspension of energy production, drought does not affect the other sub-sectors such as rail and aviation as much. In Table 7, we demonstrate how we integrate flood map with rail hotspot analyses. The same method is applied to all other infrastructure assets.

---

[5] For detailed drought methodology, please refer to the Atlas of Natural Disaster Risk of China (Shi 2011).

Table 7. How we integrate flooding and drought hazard maps with hotspot analyses – a demonstration of the rail sub-sector

<table>
<tr><td colspan="2">Step 1: flooding risk on the left; rail hotspot analysis on the right</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">Step 2: Reclassify images
Integrate rasters with a common scale. We adopt the scale of 1 to 8 by increments of 1, 8 being the most likely to be flooded or containing the highest concentrations of users.</td></tr>
<tr><td></td><td></td></tr>
<tr><td colspan="2">Step 3: Weighted overlay
Combining the two images provides us with an integrated map showing vulnerable areas according to both high flood risk and concentrations of users for the rail sub-sector.
</td></tr>
</table>

5.4. Results

Our results are divided into three main sections: (i) integrated spatial analysis for both flooding and drought impacts in section 5.4.1; (ii) sector exposure to flooding and drought impacts with respect to concentration of users, presented in section 5.4.2; and (iii) infrastructure exposure both with respect to space and users, but not considering flooding and drought impacts in section 5.4.3.

5.4.1. Integrated analysis

Flooding and infrastructure hotspots overlaid

The integrated analysis combines flooding risk analyses with infrastructure vulnerability for sub-sectors including rail, aviation, shipping, electricity and wastewater (refer to Figure 15). At a provincial level, Anhui, Beijing, Guangdong, Hebei, Henan, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang[6] exposed to flooding risks; at a city level, 66 cities are highly exposed (refer to Appendix 2).

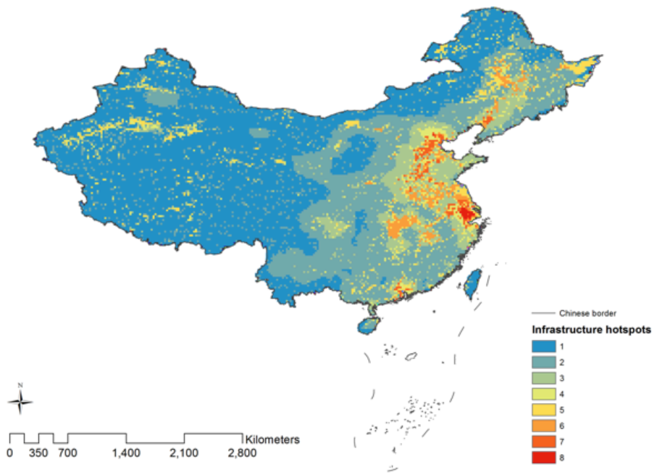


Figure 15. Infrastructure vulnerability (rail, aviation, shipping, electricity and wastewater sub-sectors) combined with flooding hazard.

[6] Exceptionally exposed is defined as provinces that are located in areas where their infrastructure hotspot values are either 7 or 8.

Drought hazard and infrastructure hotspots overlaid with the electricity sub-sector

The results shown in Figure 16 demonstrate that southern border of Inner Mongolia, Shandong, Shanxi, Hebei, north Henan, Beijing, Tianjin, southwest of Jiangsu are areas that are especially vulnerable. At a city level, the 99 cities that are at high drought exposure are listed in Appendix 3.

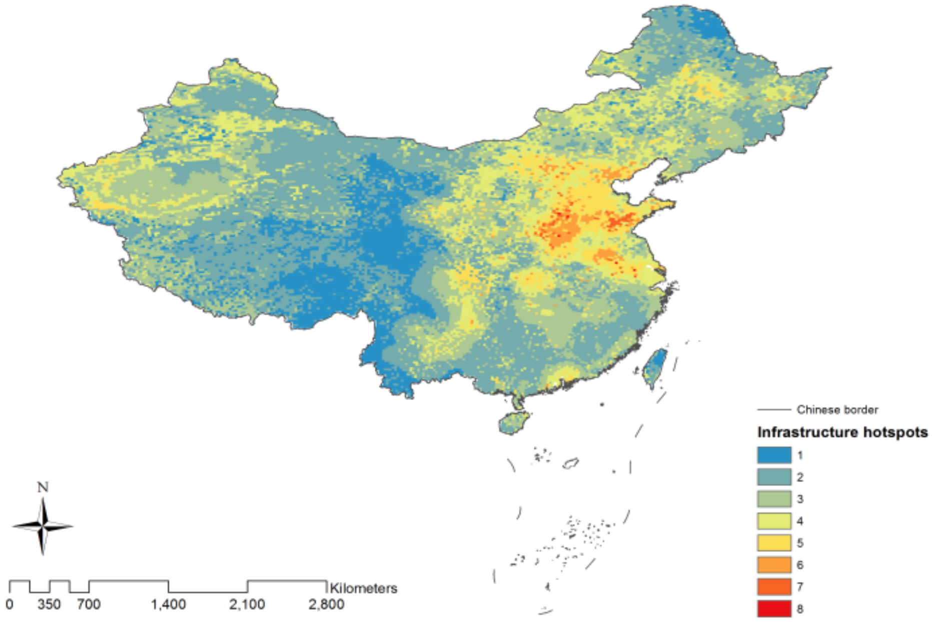


Figure 16. Infrastructure vulnerability for the electricity sub-sector combined with integrated drought hazard map.

5.4.2. Sub-sector vulnerability to flooding and drought risks

In terms of concentration of users, Tables 8 and 9 show that although most infrastructure assets are not situated in high flooding risk and drought hazard zones, the number of potentially vulnerable users is still high. For flood risk level 8, the average number of vulnerable users for all infrastructure sub-sectors stands at 144,306,112; for drought risk level 8 in the electricity sub-sector, it stands at 6,279,536. Among all sub-sectors, the most vulnerable to flooding risks are electricity and wastewater (20% and 14% of the total respectively).

Table 8. Number of users at various levels of flood risks for different infrastructure sub-sectors

Sub-sector \ Flood risk	1	2	3	4	5	6	7	8	Total
Aviation	291,619,609	6,990,327	75,711,792	83,561,261	17,110,043	1,560,574	**73,943,630**	**13,737,840**	564,235,076
	(52%)	(1%)	(13%)	(15%)	(3%)	(0%)	**(13%)**	**(2%)**	(100%)
Shipping	27,012,860	801,300	797,400	4,320,603	-	1,125,500	**4,605,940**	**2,680,800**	41,344,403
	(65%)	(2%)	(2%)	(10%)	(0%)	(3%)	**(11%)**	**(6%)**	(100%)
Rail: stations	671,600,000	108,770,000	101,835,000	51,100,000	69,715,000	43,435,000	**83,220,000**	**104,755,000**	1,234,430,000
	(54%)	(9%)	(8%)	(4%)	(6%)	(4%)	**(7%)**	**(8%)**	(100%)
Rail: tracks	3,070,120,850	378,748,455	272,920,963	262,712,522	76,540,743	78,729,162	**136,856,385**	**580,538,583**	4,857,167,663
	(63%)	(8%)	(6%)	(5%)	(2%)	(2%)	**(3%)**	**(12%)**	(100%)
Electricity	4,159,171	104,020,763	57,603,751	79,497,170	23,599,016	40,907,770	**36,924,261**	**84,214,943**	430,926,845
	(1%)	(24%)	(13%)	(18%)	(5%)	(9%)	**(9%)**	**(20%)**	(100%)
Wastewater	246,028,474	50,432,863	52,204,668	41,317,539	25,317,148	39,310,588	**35,828,988**	**79,909,505**	570,349,773
	(43%)	(9%)	(9%)	(7%)	(4%)	(7%)	**(6%)**	**(14%)**	(100%)

*We standardise user numbers on a yearly basis. For train stations, we multiply daily passenger numbers by 365 days.
For rail tracks, we calculate the percentage of rail tracks exposed to different levels of flood risks, and multiply this by the total number of passengers per year[7].

[7] Note that the number for rail track is very large. This is because it's an estimate of potential disruption which includes the passenger numbers and frequency. For details, please refer to Section 8.3.3.

Table 9. Number of users at various grades of drought risks for the electricity sub-sector

Sub-sector \ Drought risk	1	2	3	4	5	6	7	8	Total
Electricity	579,710,487	89,543,435	97,168,568	104,493,014	58,790,810	37,893,280	**6,798,672**	**6,279,536**	977,962,351
	(59%)	(9%)	(10%)	(11%)	(6%)	(4%)	**(1%)**	**(1%)**	(100%)

*We standardise user numbers on a yearly basis.

5.3.2. Infrastructure vulnerability

Overall infrastructure exposure

Not taking into account flooding or drought hazards, infrastructure exposure alone is concentrated around the south of Beijing, northern Tianjin, southern Jiangsu, Shanghai, and northern Zhejiang provinces (Figure 17). The 18 cities that are exceptionally vulnerable are listed in Appendix 4.

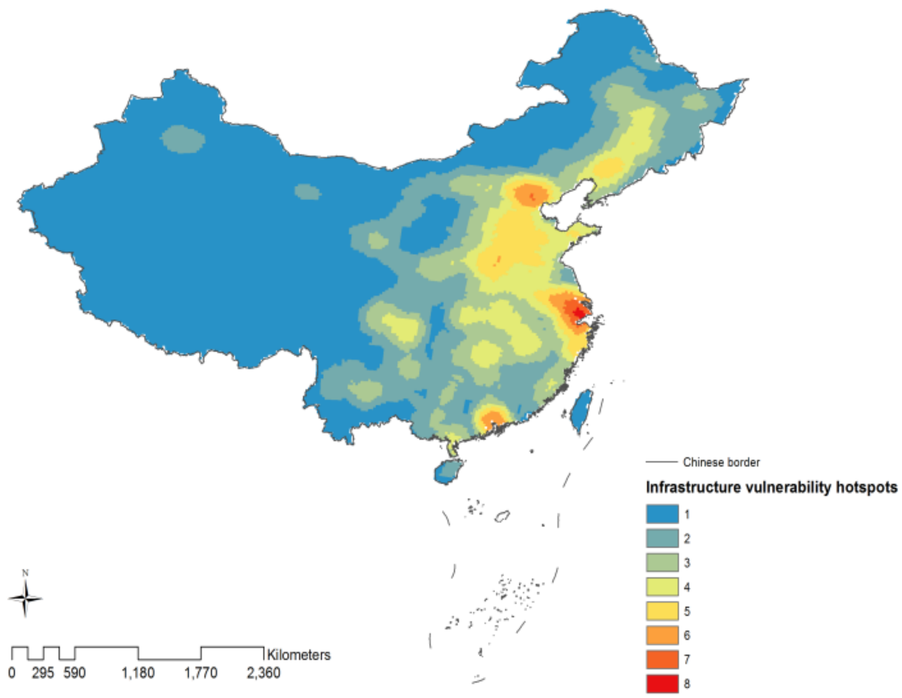


Figure 17. Composite infrastructure vulnerability using the "Overlay" tool (rail, aviation, shipping, electricity and wastewater sub-sectors)

Sub-sector exposure

One can also observe infrastructure exposure separately by looking at different sub-sectors (Figures 18-21). For the rail sub-sector, the analyses for rail stations (Figure 18, left) and rail tracks (Figure 18, right) reflect similar hotspots in that Beijing is highly vulnerable. However, using train timetable information represents a better understanding of vulnerable hotspots such as Shanghai, Hubei, Shandong and Henan, through which substantial traffic passes, are also identified. The results for aviation (Figure 19, left) and shipping (Figure 19, right) are not surprising – the airports and ports that take the most passengers are identified as vulnerable hotspots. For the electricity sub-sector, north Henan, south Shanxi, south Jiangsu, Anhui, Shanghai, west Hubei, south Guangdong are vulnerable provinces (Figure 20, left). In addition, we successfully identify the surplus producing provinces in Figure 20 (right), highlighted in green. For wastewater, south Hebei, coastal Shandong, eastern Henan, northwest Anhui, south Jiangsu, and north Zhejiang are the most vulnerable provinces (Figure 21).

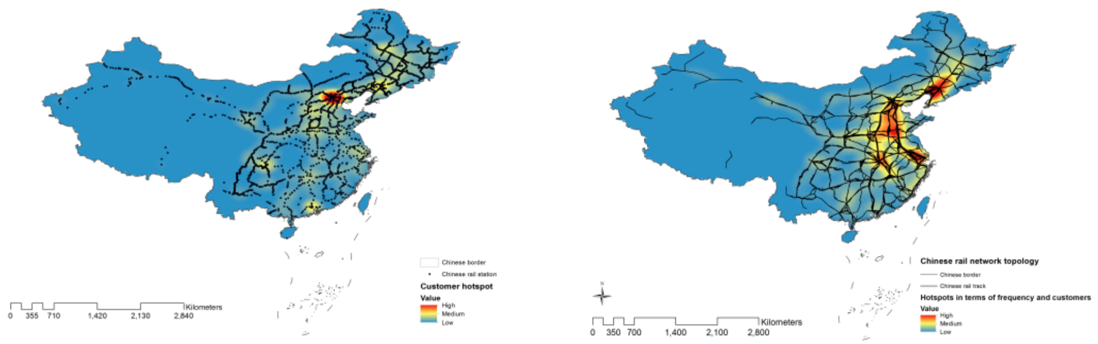


Figure 18. Rail stations user hotspot analysis at 200,000 km search radius (Left). Rail track user hotspot analysis at 200,000 km search radius, based on use frequency of rail tracks and number of users (Right)

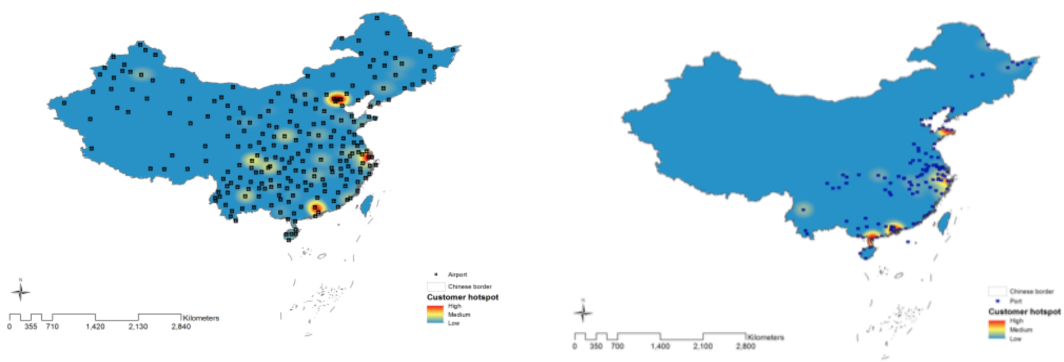


Figure 19. Airport user hotspot analysis at 200,000km search radius (Left). Port user hotspot analysis at 200,000km search radius (Right)

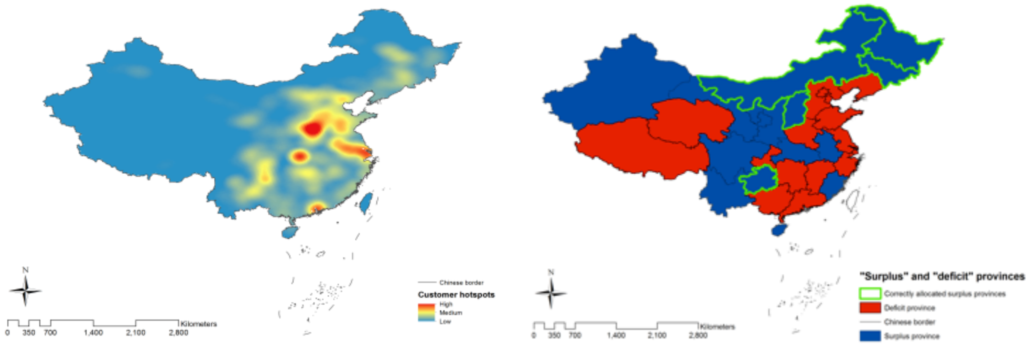


Figure 20. Power stations user hotspot analysis at 200,000km search radius (Left). Successfully allocated five provinces that are "surplus" provinces, highlighted in green (Right).

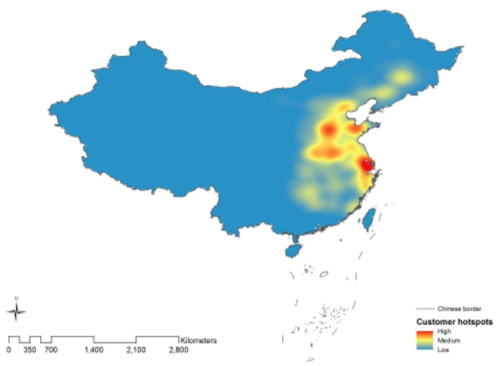


Figure 21. Wastewater subsector hotspot analysis at 200,000km search radius.

The potential number of users affected is very high for the rail, electricity and wastewater sub-sectors, as shown in Table 10. However, it is important to note that our database for shipping is incomplete; therefore the real exposure may be significantly higher than that presented here. The results exhibited in this section do not include any hazards and can be used for further analysis for other disasters such as landslides.

Table 10. Potential number of users affected in different infrastructure assets in a year

Infrastructure assets	Number of users	Percentage of total population (%)
Rail stations	439,825,000	33.0
Rail tracks	111,120,600	8.34
Port	1,529,350	1.15
Airport	321,766,557	24.2
Electricity	451,202,612	33.9
Wastewater	315,478,372	23.7

5.5. Discussion

The purpose of this study is to understand how the Chinese infrastructure system is exposed to flooding and drought impacts. In particular, we seek to provide insights into the locations of critical infrastructure at risk to flooding and drought impacts on a broad scale, and estimate the potential number of users affected on the local scale should infrastructure assets fail owing to one or a series of flooding/drought event(s).

Several assumptions are required in order to locate critical infrastructures. First, we assume an infrastructure system consisting of five sectors – energy, transport, water, waste and ICT. Although this taxonomy approach is necessary to help us restrict the scope of our analysis, it inevitably leaves some infrastructure assets such as buildings yet to be studied.

Second, we assume that trains are operating at full capacity when allocating passenger numbers to individual rail tracks. This is a valid assumption, as most trains in China are in fact operating beyond their designed capacities. According to Xinhua News, the official news channel for China, the national average passenger attendance is 133% and 120% for rail services (Yin 2010). Therefore our assumption of 100% is reasonable and in fact represents an underestimate of the real exposure of rail assets to flooding/drought hazards.

Third, owing to very limited data on national-scale transmission grids in China, we assume that generation capacity in a specific region directly supplies a specific number of people in that region. This is a limitation in our work because we are not able to take into account energy flows between regions and our results consider hazard impact on generation and not transmission. However, with approximately 20% of electricity produced nationally is being transferred across provinces, we believe our analysis focused on generation impact still represents the reality reasonably (State Grid Energy Research Institute 2014). Future research will require a better understanding of the transmission networks given China is building many “Ultra High Voltage” transmission networks that are able to transfer electricity across three or four provinces at a time (*Ibid*).

In addition to the assumptions discussed above, we use a global flooding risk model developed to prepare the flood hazard map (Yamazaki et al. 2011). This is owing to the lack of a national-level flooding risk assessment with hydrological modelling at the time of this study. The limitations of using global flooding risk models have been discussed extensively by Ward et al (2015). Future work could look into comparing the risk map with alternatives such as the global flood risk map by Ward and others, or the Pappenberger and others’ global flood hazard map by the Hydrology and Earth System Science, or the national flooding risks mapping efforts by the Chinese Ministry of Water Resources[8] (Pappenberger et al. 2012; Ward et al. 2013). In addition, the flood calculations do not account for flood defence because of poor documentation of data for China and elsewhere (e.g., see Supplementary Table 2 in Jongman et al. 2014). More work is required to understand how flood infrastructure changes flooding and drought risks on the national scale.

[8] Personal communication with the Chinese Ministry of Water Resources indicated that a national-scale flooding risk map should be available by 2017.

Despite the aforementioned assumptions and limitations, our results inform policy making by identifying locations of critical infrastructures exposed to flooding/drought impacts on the national-level. We find that at a provincial level, Anhui, Beijing, Guangdong, Hebei, Henan, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang; at a city level, 66 cities are at high risk. This is for sub-sectors including rail, aviation, shipping, electricity and wastewater. For drought, we demonstrate that southern border of Inner Mongolia, Shandong, Shanxi, Hebei, north Henan, Beijing, Tianjin, southwest of Jiangsu are areas that are especially vulnerable. At a city level, 99 cities are at high risk.

The above exposed regions are to some extent not surprising because they are all highly urbanised and have experienced exponential growth in infrastructure assets. To see this, we overlay the infrastructure hotspots with a map of the urbanisation extent in 2012 using DMSP-OLS night time light data (NOAA 2015). The urban extent is used as a reference against the hotspot analysis. In fact, Figure 22 demonstrates that our infrastructure hotspots capture the urban areas very well – all our red and yellow hotspots are located in areas where the lighted regions are. The exception of the area highlighted in the orange circle may be caused by a lack of infrastructure data. Interestingly, our hotspot map highlights the south coast (the green oval-shaped circle in Figure 22) as highly exposed in terms of critical infrastructures. The urban extent map is unable to reveal this insight because it relies on streetlights being captured by satellites i.e. if the streetlights are spread across a large area, the night time map will not be able to identify urban areas that have many critical infrastructures. Thus, our analysis provides additional insights to conventional exposure studies that solemnly rely on population or urban data.

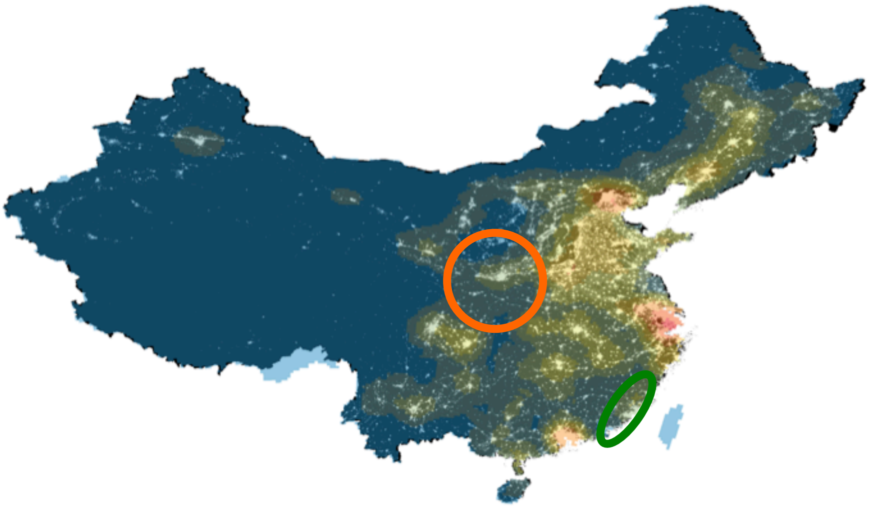


Figure 22. Urbanisation extent using DMSP-OLS night time light data from 2012[9].

To make a further comparison, we overlay a population density map (Figure 23a), which is often used to identify the locations of critical infrastructure demands, with our infrastructure hotspot analysis. In Figure 23b, we find that our integrated infrastructure hotspot map fits the population density reasonably well (black dots are populated areas and red spots are infrastructure hotspots). However, the population density map is unable to identify sectoral differences which are spatially variant in nature, as shown in Figure 24. The most notably mismatch occur in the port and rail track assets. This is because ports tend to be located near rivers whereas population dense regions may not be. Our rail track hotspot analysis demonstrates connectivity which population density maps are not able to capture.

[9] Two national boundaries do not match because one is extracted from the Atlas of Natural Disasters in China which includes Taiwan and Arunachal Pradesh; the other is from US National Oceanic and Atmospheric Administration.

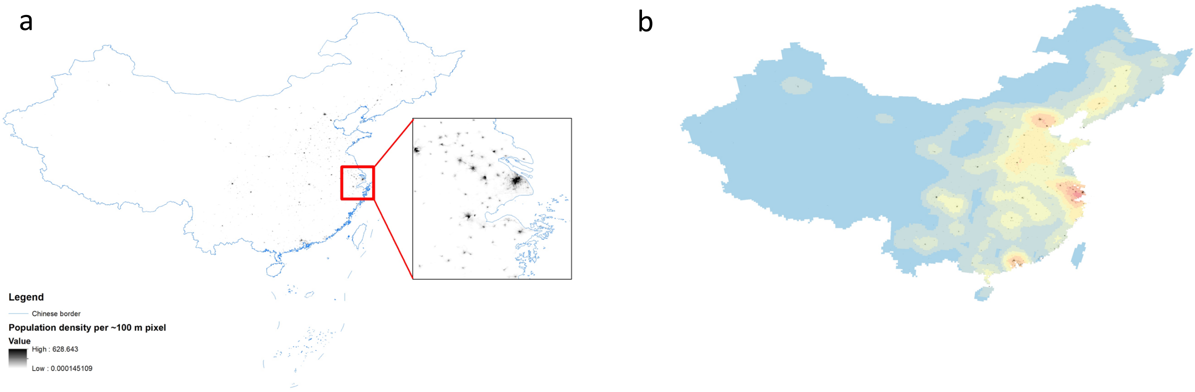
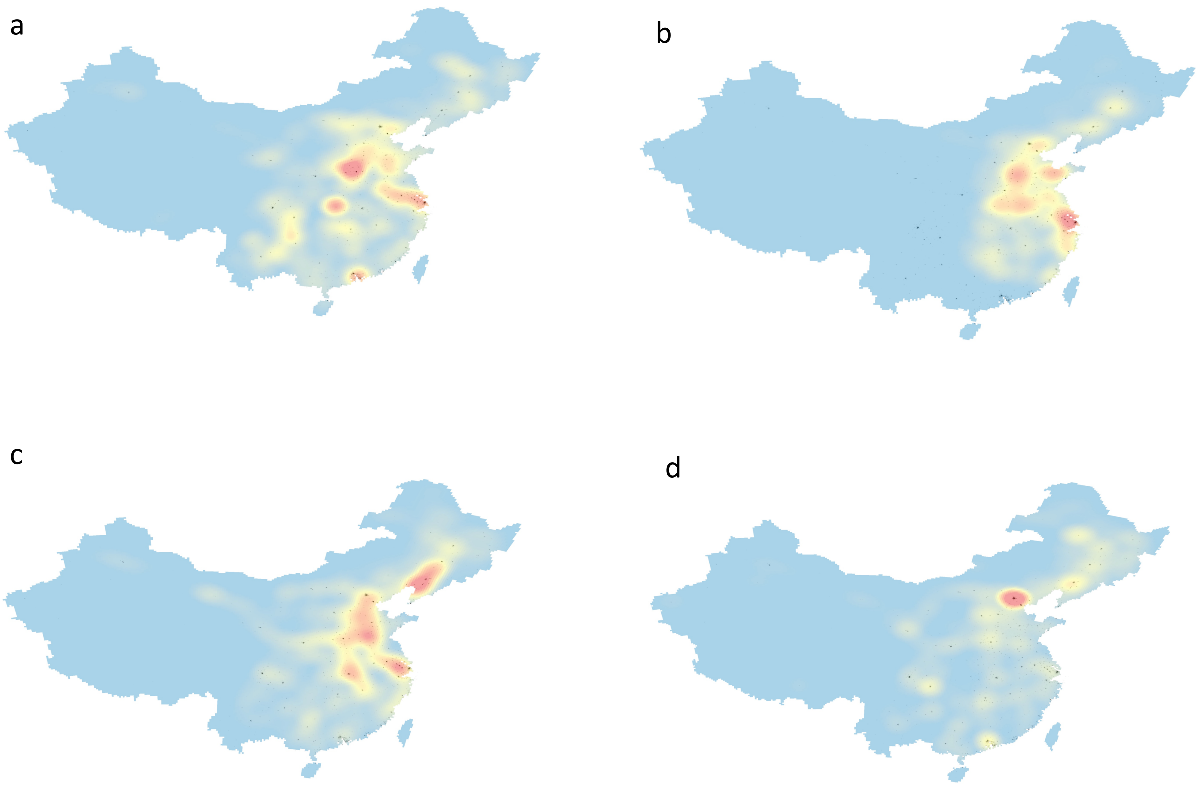


Figure 23. Population density map at ~100 m per pixel for China (Figure 23a). Comparison between the integrated infrastructure map with population density map (Figure 23b).

Source: WorldPop.org (2018)



e

f

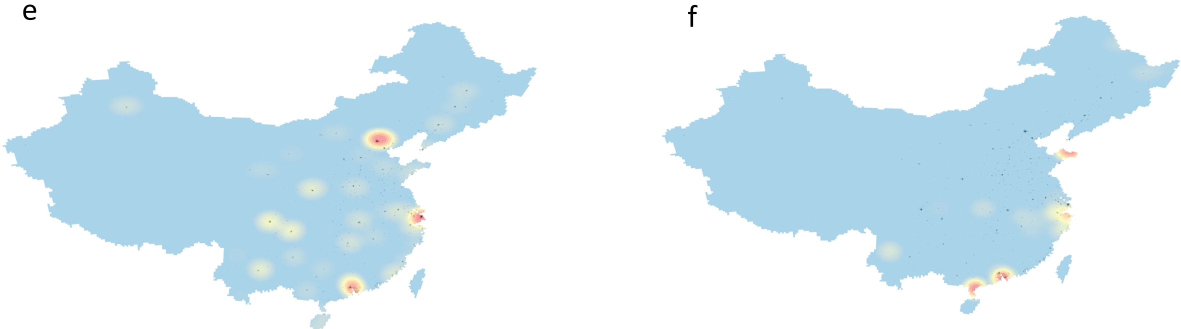


Figure 24. Population density map compared to power plants (Figure 24a), waste treatment plants (Figure 24b), rail tracks (Figure 24c), rail stations (Figure 24d), airports (Figure 24e) and ports (Figure 24f).

In terms of policy implications, our analysis provides scientific evidence for mandating disaster risk reduction in China as we demonstrate the scale of the potential number of people affected. For flooding, the average number of vulnerable users for the above sub-sectors stands at 103 million and the most vulnerable are electricity and wastewater (20% and 14% of the total respectively). For drought risks, the number of exceptionally vulnerable users for the electricity sub-sector is 6.5 million. As such, the work could help regional leaders be informed of their potential vulnerabilities and exposure.

5.6. Conclusions

Infrastructure growth has not only contributed enormously towards China's growth, but also hindered it during periods of failures when natural disasters such as flooding and drought have occurred. Given that infrastructure development remains a top priority for China's government and climate change is projected to aggravate the impacts of natural disasters, understanding the exposure and vulnerability of these assets has become increasingly important.

Unfortunately, it is not easy to study the exposure and vulnerability of the infrastructure system at a national scale in China for two main reasons. First, data on infrastructure assets are very limited. Even when they do exist, often they are in Chinese and spread across different data sources such as national/regional/local statistical yearbooks. This is perhaps why existing literature has been restricted to city-scale analyses and broader scale studies tend to be focused on one sector only. Second, the infrastructure system consists of many sectors that make comparisons of exposure and vulnerability between them difficult.

Our work has addressed the former challenge by taking a first step to look at infrastructure exposure and vulnerability on the broad scale. To do this, we have built a database consisting of 10,561 nodes and 2,863 edges across three different infrastructure sectors and networks. We have developed a methodology that creates a common metric i.e. concentration of users based on empirical data where possible, which helps us compare vulnerability across different infrastructure sectors from a systems perspective despite the nature of disruption can vary among sectors. This approach could be used to study other natural disasters that are common in China, such as snowstorms and landslides.

As already discussed earlier, one limitation of this paper is that the results may not show all infrastructure hotpots because in some cases we have incomplete datasets on infrastructure assets. Therefore the results presented may be an underestimate of infrastructure exposure and vulnerability. In addition, although sufficient for a national assessment, the resolution for flooding and drought analyses is not high. Further, we are not able to capture inter-provincial electricity transfer for our electricity "hotspot" analysis, as we do not have data on national-scale transmission networks. Moreover, we resort to using the results from a global flooding risk model as a national-scale study based on hydrological modelling is not available at the time of study.

Despite the limitations, this work is useful for informing strategic infrastructure planning and the methodology applied here can be transferred to other geographical areas on the national-scale. Future work will attempt to look at how this spatial exposure may change given further urbanisation and climate change impacts.

6. Multi-scale assessment of the economic impacts of flooding on the Chinese manufacturing sector: firm to macro level analysis

6.1. Introduction

Flooding has a huge impact on the socio-economic well-being of nations. Between 1900 and 2011, China suffered 207 recorded flood events, which cumulatively affected 1.8 billion people (Chen et al. 2013). In some of the more economically developed coastal provinces in China, flood costs at city and industrial levels accounted for more than 60% of the total flood losses (Ministry of Water Resources, 2012).

The Chinese manufacturing sector is particularly vulnerable to flooding, as many of the sites are located in southern China, which is a particularly flood-prone region. In 2016, the manufacturing purchasing managers' index fell to 49.9 in June, below the 50-point line delineating growth for the first time in four months (Lockett 2016). The primary factor causing the contraction was considered to be heavy rains and flooding in most of China's provinces, particularly those along the Yangtze River Basin, which had impacted production (down 0.4 percentage points to 52.1) and transportation, among other things (*Ibid*).

Such problems are not confined to China. Thailand's 2011 floods alone inundated seven industrial parks in which 804 companies operated (Haraguchi & Lall 2015). 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 in the country. Not only was Thailand affected; the floods reduced the world's industrial production by 2.5%, owing to the interconnectivity between global suppliers (UNISDR 2011).

Given the significance of these costs, the proper estimation of flood losses has been the subject of extensive analysis (Poljanšek et al. 2017; Meyer et al. 2013; Kreibich et al. 2014; Jongman et al. 2012; Hallegatte 2008; Rose & Liao 2005; Van Der Veen & Logtmeijer 2005). However, what we know much less about is the systemic impacts of floods at business level. Most of our information comes from news reports, surveys or interviews about the costs to individual businesses, often in terms of reports of accidents, the production losses to firms resulting from particular floods, and the costs of repairing/replacing damaged property, business closure and/or insurance pay outs for different sectors (Kreibich et al., 2007; Tierney & Nigg 1995). We also know little about the wider macroeconomic impacts resulting from disruptions at firm level.

The objective of our paper is to quantify the economic consequences of systemic disruptions to manufacturing firms due to flooding and the associated wider macroeconomic loss propagation effects. To this end, we present a data-driven framework that integrates econometric analysis with macroeconomic modelling. First, we calculate the impact of flooding on the Chinese manufacturing sector by conducting a regression analysis of Chinese flooding data from 162,830 manufacturing companies between 2003 and 2010, which provide a reasonable representation of the manufacturing sector of China for the period of analysis considered here. The regression analysis quantifies the relationship between large-scale flooding events and firm-level productivity losses across the manufacturing sector. This is the first empirical study we are aware of which employs econometric techniques to systemically estimate flooding impacts at firm level across the whole of China.

Second, using economic input-output analysis, we estimate the potential propagation of firm-level disruption effects to the rest of the Chinese economy. The mechanisms of flood damage leading to business disruption and economic loss propagation are highly complex. They may include, but are not limited to, direct damage to capital, loss of stock, and business interruptions (e.g. factories being out of business and/or workers being unable to get to work) (Kousky 2014). In particular, manufacturing companies provide essential inputs to the production processes of other economic sectors. For instance, the fabricated metal industry, which is a sub-sector of manufacturing, produces iron, steel and various metals that are used in the construction industry for building roads and other types of transport infrastructure. The manufacturing sector also makes plumbing pipe parts which are essential for water supply infrastructure and providing boilers for electricity and heat production (National Bureau of Statistics of the

People's Republic of China 2017). Owing to this input-output production relationship, if the manufacturing sector is unable to produce due to a flood event, production in other sectors could be affected, which would lead to further economic losses. Even if the manufacturing firms are not flooded themselves, their operations may still be affected because they are located in flooded areas, which could then lead to propagating impacts on those sectors that rely on the manufacturing sector. Through the economic input-output analysis we have captured such propagation impacts. Although the data and analysis are presented for China, our framework and methods are applicable to other contexts around the world.

The rest of the paper may be outlined as follows. In Section 6.2 we present the relevant literature on flood impact assessment modelling approaches, highlighting the current state of progress and gaps in economic impact assessment. This sets up Section 6.3, where we present our framework approach, highlighting the main modelling principles and components. Section 6.4 presents the data on China's manufacturing sector used for our case study, followed by the econometric analysis. Section 6.5 explains how we estimate the wider macroeconomic impacts through an input-output model analysis. In Section 6.6 we present the results of the analysis. Section 6.7 presents the conclusions and further steps for this study.

6.2. Literature review

In the literature, the economic impacts of natural disasters have been classified in different ways due to differing views on how these impacts are perceived in different research communities (see Penning-Rowsell et al. 2003; Merz et al. 2010; Kreibich et al. 2014; Meyer et al. 2013; Kousky 2014). In this study, we adopt the categorisation of economic losses into the following types of costs (Kreibich et al. 2014; Meyer et al. 2013): (1) *direct costs* – the costs incurred due to physical damages of assets due to susceptibility to flooding; (2) *business interruption costs* – the costs incurred in hazard areas when people are not able to carry out their work because their workplace is either destroyed or made inaccessible; (3) *indirect costs* – the costs incurred inside or outside hazard areas with a time lag, when, for instance, there are production losses to suppliers and customers of the companies that suffer direct or business interruption losses; (4) *intangible costs* – types of damages that are not easily measurable in monetary terms such as environmental impacts, health impacts and impacts on cultural heritage; and (5) *risk mitigation costs* – any costs attributed to the operation, maintenance, research and development of risk mitigation infrastructure, or other measures for the purposes of risk mitigation; or any secondary costs (externalities) occurring in economic activities or localities that are not directly linked to such infrastructure investment.

The particular focus of this paper is on business interruptions and their resulting indirect costs. It should be noted that there is no consensus in the literature regarding the classification of business interruptions; some studies include business interruption costs within direct costs (Merz et al. 2010), while others include them as indirect costs (Carrera et al. 2015; Kousky 2014; Rose & Liao 2005). Since they are measured in a different way from both direct and indirect costs, they need to be treated as separate (Kreibich et al. 2014; Meyer et al. 2013). Similarly, intangible costs and risk mitigation costs are sometimes not explicitly classified and may be accounted as direct or indirect impacts (Kousky 2014).

Over the last decade or so a range of different methods have been developed to assess the economic impacts of natural disasters that include flooding (see Table 11). These methods primarily focus on estimating direct and indirect economic losses, with other effects included within these two categories. A particularly common approach for estimating direct damage losses is event analysis – both ex-ante and ex-post – which uses empirical and qualitative approaches to create damage-curves for general classes of residential or business buildings, equipment, and inventory stocks for different levels of flooding (depth or discharge) to estimate economic impacts of flooding events (Tierney & Nigg 1995; Kreibich et al. 2007; Molinari et al. 2014; Ayyub et al. 2012). Event analysis model outputs are generally useful inputs for other models that estimate direct and indirect losses.

Amongst the methods most widely used for estimating direct and indirect economic flow losses are Computable General Equilibrium (CGE) and Input-Output (IO) based approaches, which work at macro scales. CGE models have been used for disaster impact analysis because they are able to model non-linearly the behavioural response to price changes, input and import substitutions and supply constraints (Rose & Liao 2005; Mechler et al. 2010; Okuyama & Santos 2014). CGE models capture indirect economic losses because they consist of a system of equations which describe the behaviour of the economic agents (representative household and firm), the structure of the markets and the institutions, and the links between them (Carrera et al. 2015). The IO-based models are linear models working on the premise that each industry produces goods and consumes goods from other industries in order to produce such goods, thus has strong capabilities of capturing the interdependence of economic sectors upstream and downstream the supply chain of the disrupted goods (Hallegatte 2008; Hallegatte 2014; Jenkins 2013). While traditional IO models have been critiqued for their linearity and simplistic demand-driven approach (Rose 2004), over the years several hybrid IO models have been developed to incorporate, among others, non-linearity, supply-side effects, and substitutions (Hallegatte 2008; Jenkins 2013; E. E. Koks et al. 2015).

Econometric techniques, which are statistical methods, are also widely used to estimate the impacts of natural disaster events, mostly at macro scales. These methods do not make a distinction between direct and indirect impacts, but instead concentrate on indicators of total economic activity such as GDP (Coelli & Manasse 2014). Most find a negative impact from disasters on the economy, the extent of which depends on the size of the shock, how strong the institutions are, and how diversified the economies are, as well as the length of time after a disaster, among other factors (Hochrainer 2009; Schumacher & Strobl 2011; Raschky 2008; Kocornik-mina et al. 2015). In terms of the time frame, econometric models on the impacts of natural disasters are mostly on economic growth/productivity both for the short run and long run whilst others look at the impact on individuals and firms (Hochrainer 2009; Coelli & Manasse 2014; Kocornik-mina et al. 2015).

Overall, different methodologies serve different purposes and there are advantages and disadvantages associated with all. There are still major gaps in economic impact assessment methods that need addressing. Here we identify gaps specific to measuring business disruptions and indirect impacts. Firstly, business disruption losses, along with intangible and other losses, are rarely measured, as direct damage losses receive a relatively large amount of attention (Meyer et al. 2013). Secondly, the reason there is a lack of studies on business disruption losses is that detailed, reliable and comparable data on ex-ante business activities and ex-post event losses are usually unavailable (Kreibich & Bubeck 2013; Meyer et al. 2013). Thirdly, economic losses due to business disruptions have mostly been empirically analysed at aggregated regional or national sector levels (Fomby et al. 2013), with few studies at firm level being done (Coelli & Manasse 2014). Fourthly, though most direct losses are estimated in terms of asset damage, economic flow losses are considered more consistent with macroeconomic measures such as GDP (Rose 2004). Finally, due to the poor quality of the direct losses input data, macroeconomic indirect loss estimation models often produce vastly varying estimates, even for the same disasters (Hallegatte & Przyluski 2010).

The methodology in this paper aims to address these gaps. Since we are interested in measuring the economic losses of firm disruptions and how these propagate throughout the rest of the economy, we find that we must combine existing approaches. As stated previously, econometric approaches have provided a basis for quantifying business disruptions, while macroeconomic models are the best available tools for measuring indirect losses. Hence, we employ a combination of these two approaches, the process and rationale for which is explained in the next section.

Table 11. A summary of methods available to assess the economic impacts of natural disasters

Method	Spatial scale	Scholarly works
Event analysis	Individual, firm, sector	Tierney & Nigg 1995; Suarez et al. 2005; Kreibich et al. 2007; Molinari et al. 2014; Kreibich et al. 2010; Ayyub et al. 2012
Computable General Equilibrium (CGE)	Global and national	Rose & Liao 2005; Mechler et al. 2010; Carrera et al. 2015
Input output (IO) analysis	Global/National/regional	Van Der Veen & Logtmeijer 2005; Crowther et al. 2007; Yamano et al. 2007; Hallegatte 2008; Jonkman et al. 2008; Pérez & Barreiro-Hurlé 2009; Rose & Wei 2013; Hallegatte 2013; Jenkins 2013
Econometric techniques	All	Raschky 2008; Craioveanu & Terrell 2009; Hochrainer 2009; Schumacher & Strobl 2011; Vu & Noy 2013; Yamamura 2013; Coelli & Manasse 2014; Kocornik-mina et al. 2015

6.3. Framework overview

For our analysis, we have assembled individual ex-ante and ex-post flood-affected firm-level data and employed econometric techniques to estimate the firm-level disruptions. This is done at a detailed spatial granularity, which is a significant improvement on previous studies. The data cover an exhaustive list of firms in China that to our best estimates describe business activities of entire macroeconomic sectors, all of which are engaged in different types of manufacturing activities. A larger set of multiple sectors has also been empirically studied, compared to previous micro-level studies.

Figure 25 shows our framework, which quantifies the economic losses due to firm-level disruptions and the associated propagating interruptions to other sectors. The framework is capable of assessing the economic impact of flooding at various spatial scales – firm, local, industry, meso, national, and macro. It has three components: (A) Firm-level analysis – when businesses are in local areas where there has been a large-scale flooding, their ability to operate and maintain supply can be affected, producing economic losses. We use productivity, a measure of output, to indicate firm-level losses through measuring performance before and after flooding events. (B) Sector level analysis – firms belonging to different economic sectors are aggregated to estimate the effects of their disruption on the sectors' performance. Each economic sector at a wider national scale, comprised of all firms within that particular sector, suffers direct economic flow losses when there are substantial numbers of firms affected by large-scale flooding. This could be due to the inability of the sector as a whole to maintain the supply level by substituting and increasing the productivity of unaffected firms. We look at this productivity loss for entire sectors. (C) Macroeconomic level analysis – the entire national economy comprised of multiple sectors, government and households suffer indirect economic flow losses due to economic interdependence. We estimate these losses through an input-output model that translates productivity losses into direct supply side flow disruptions to estimate the indirect impacts.

In the next sections, we explain and demonstrate how we apply the econometrics and input-output modelling techniques to estimate the impacts of flooding on firms in

China. Our rationale for using a combination of these models for firm-impact is as follows. Econometrics analysis is used because it has the advantages of giving empirical content to economic theory and being able to test hypotheses (Wooldridge 2003). We can thereby empirically test if firms have been affected by disasters. If the disaster variable is significant, we can use the empirical data to estimate the extent to which the firms have been impacted. Another advantage of econometric techniques is that they can examine the relationship between variables over time, in particular, assessing lagged effects of a particular "shock" with panel analysis. This is preferable to approaches such as event analysis, which is only applicable to very short-run impacts. Other methods to estimate firm-level impacts – post event surveys, econometrics techniques and CGE models – may also be used. If well specified and based upon data of a reasonable quality, post-event surveys can indeed quantify the effects of extreme events on businesses. However, they typically cover one event only (Przyluski and Hallegatte 2011) and are limited in scale in terms of the number of firms that can be studied. Although CGE models can capture market behaviour, they tend to have a "coarse" investigation unit, usually the country (Rose & Liao 2005). This may allow analysis of aggregated events or trends, but makes local analyses, especially individual firms, particularly challenging.

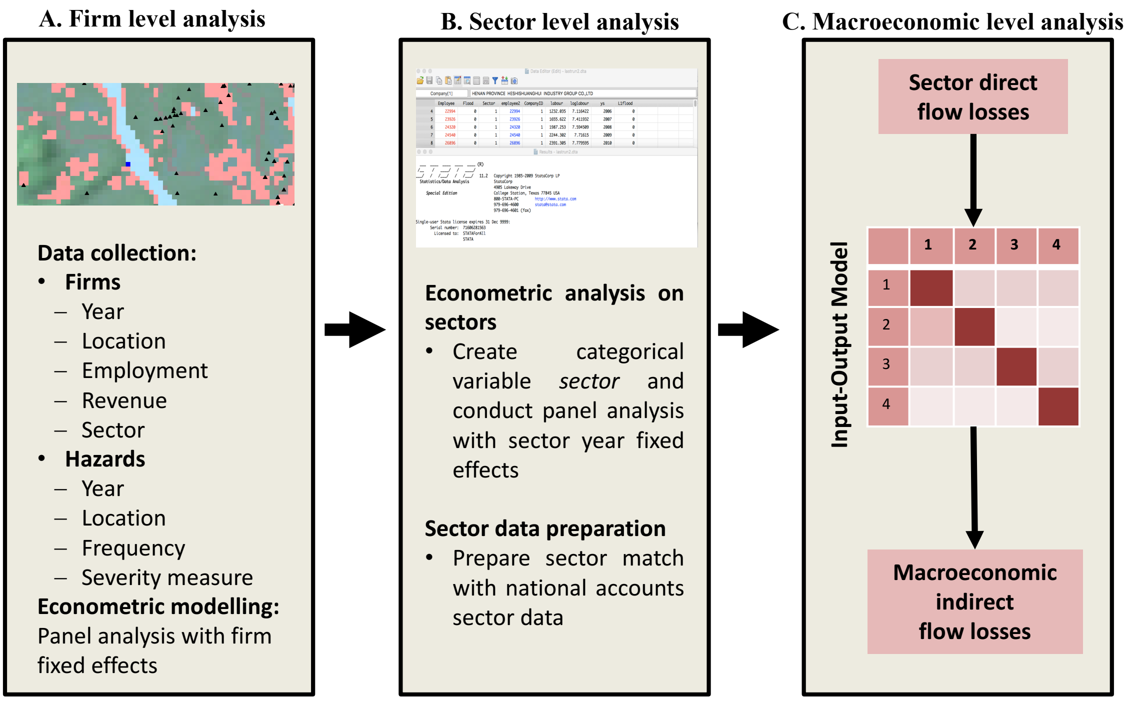


Figure 25. Overview of framework

To address the question of propagating indirect effects from firm-level to sector and broader levels, econometrics, CGE models and input-output analysis can all be potentially applied. Theoretically, one may use interaction effects to test how one variable affects another in econometrics, for example, we could test the output impact on infrastructure sectors due to the combined effects of flooding and a reduction in manufacturing sector output. However, this would require extensive data covering all the firms in the infrastructure sectors concerned, which are difficult to obtain. Hence, due to the complexity of data and modelling requirements, econometric models have generally avoided estimating direct and indirect losses, concentrating rather on macroeconomic indicators such as GDP that could reflect combined effects (Coelli & Manasse 2014).

The alternatives are IO analysis or CGE modelling, which both provide insights into how sectors are interlinked. They are supported by recognised national accounting data, which are increasingly being standardised world-wide and constantly updated by governments and global agencies (Yamano & Ahmad 2006; Tukker et al. 2008; Lenzen et al. 2013). In current practice they can be considered to be the best sources for explaining macroeconomic sector interlinkages at regional, national and international scales. The fundamental difference between CGE and IO is that the input-output method is partial economic analysis, whereas CGE modelling takes a general equilibrium approach which describes the complete economy, accounting for all monetary and nonmonetary flows (Koks et al. 2015). It should be noted that both types of approach should be treated as representations of one or more particular aspects of reality, and their results highlight the influence of such aspects, rather than comprehensively explaining how the economy behaves in a disaster situation (Okuyama and Santos 2014). CGE models have been found to underestimate disaster impacts while IO models overestimate them, with reality being somewhere in between (Koks et al. 2015). CGE models are also more complex and require more data to parameterise, which often makes them difficult to apply compared to input-output models (Meyer et al. 2013). Since we are only interested in how interlinked economic sectors are affected owing to the impact of flooding on the manufacturing firms, partial analysis is sufficient. In keeping with recent IO developments, we treat firm-level disruptions as supply-side direct flow losses (Steenge & Bockarjova), thus addressing some of the short-comings attributed to traditional demand-driven IO approaches not being applicable to extreme hazard events (Jenkins 2013).

Another advantage of our modelling approach is its ability to capture uncertainties in the business disruptions and their subsequent effects on the indirect economic loss estimates. We do this by empirically estimating firm-level impacts, which gives us a confidence range of the magnitude of disaster losses on firms, and we subsequently use this to work out the macro-level impacts. Generally uncertainties in estimating business disruption losses are not well understood, while IO model outputs are mostly presented as deterministic estimates due to aggregated data estimates (Meyer et al. 2013). To our knowledge, this is the first study that combines the two models to assess natural disaster impacts.

6.4. Econometric analysis

6.4.1. Chinese firm-level and flood data

The lack of firm data means that few econometric studies have looked at the business disruption costs of flooding on firms. More importantly, those econometric studies that do exist have not been able to assess the spatial implications of impacts since the location of flooding will significantly influence how firms are affected. We obtain a large dataset on China's manufacturing sector, covering a total of 162,830 companies with detailed information on firm revenues, employees and addresses between 2003 and 2010. The number of sectors included is 24 (see Table 12).

Flooding data are collected from the Dartmouth Flood Observatory, which contains an archive of large floods in the world between 1985 and 2016 (Brakenridge 2016). A record of 128 major floods in China is selected for the period between 2003 and 2010. The flood sample in this study consists of major reported flooding events in China. These are "derived from a wide variety of news and governmental sources", and are divided into three classes – large, very large, and extreme (*Ibid*). Large flood events are defined as causing significant damage to structures or agriculture/fatalities; and/or with a decades-long reported interval since the last similar event (*Ibid*). Very large events are those with a greater than 2-decade but less than 100-year estimated recurrence intervals, and/or a local recurrence interval of 1-2 decades and affecting a large geographic region (> 5000 sq. km). Extreme events have an estimated recurrence interval greater than 100 years (*Ibid*). We use this sample of large floods because these events are the most disruptive. Whilst smaller ones from other databases may inflict direct damage, they are less likely to have a production effect on manufacturing companies. The summary statistics of the flood variables from Dartmouth Observatory used are presented in Table 13.

Table 12. Manufacturing sub-sectors included in the analysis

Sector	Name
1	Food products
2	Beverages
3	Tobacco products
4	Textiles
5	Wearing apparel
6	Leather and related products
7	Wood and products
8	Paper and paper products
9	Printing and reproduction of records
10	Coke and refined petroleum
11	Chemicals
12	Basic pharmaceuticals
13	Rubber and plastics
14	Other non-metallic metals
15	Basic metals
16	Fabricated metal products
17	Computer
18	Electrical equipment
19	Machinery
20	Motor vehicles
21	Trailers and semi-trailers
22	Other transport equipment
23	Furniture
24	Others

Source: Orbis (2017)

We georeferenced the company dataset to benchmark against flooding records. Access to this spatial data provides us with the possibility of examining the spatial impact of flooding on Chinese businesses for the first time. Figure 26 shows a zoomed-in map of the actual flooding extent between 1997 and 2010 in Guangdong province in China and the locations of manufacturing companies. Figure 27 depicts the locations of major flooding events between 2003 and 2010 and Chinese manufacturing plants. As we may observe, many cities where there are concentrations of manufacturing sites are affected by floods.

Table 13. Variable descriptive statistics of the Dartmouth major reported floods in China between 1985 – 2016

	Duration in Days	*Dead*	*Displaced*	*Damage (USD)*[10]	*Affected sq km*
Mean	11	66	289965	279	143856.55
Standard Error	1	14	63131	76	23299.46
Median	6	17	37700	37	46140.00
Standard Deviation	14	150	598912	656	263603.31
Minimum	2	0	0	-	30.00
Maximum	81	1100	3170000	4,250	1916000.00
Sum	1427	7101	26096856	20,6601	18413639.00
Count	128	108	90	74.00	128.00

Source: Dartmouth Flood Observatory, Brakenridge et al. (2016).

[10] To the nearest million.

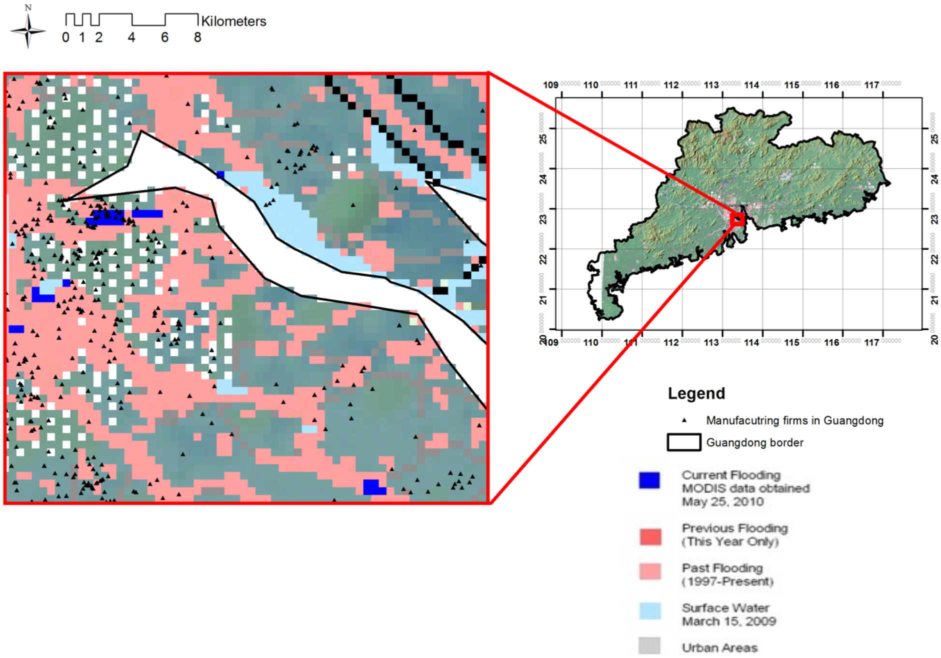


Figure 26. Location of major reported flooding events in Guangzhou.

Blue indicates the May flooding event in 2010 which was a mega event; red indicates other flooding events in 2010; pink indicates flooding events between 1997 and 2010. Manufacturing sites are shown as black triangular dots. Blank area indicates no data. Source: Orbis and Dartmouth Flood Observatory 2016.

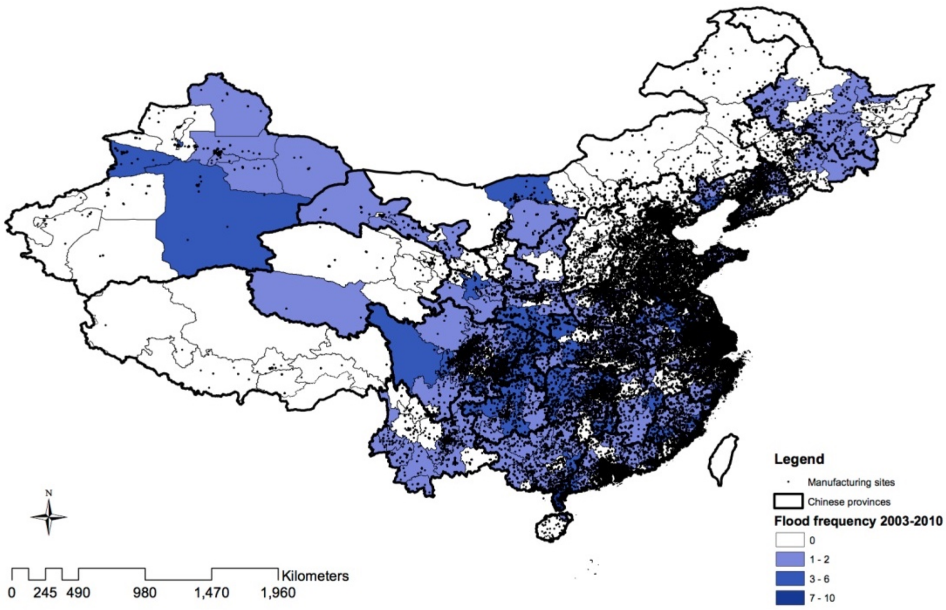


Figure 27. Location of major reported flooding events at city level between 2003 and 2010 and manufacturing plants in China.

Source: Dartmouth Flood Observatory (2016) and ORBIS (2017).

6.4.2. Empirical approach

We conduct a regression analysis of Chinese flooding data and manufacturing companies in China from 2003-2010, to test the hypothesis that flooding has an effect, i.e. impact on Chinese manufacturing companies, and estimate the magnitude of the effect. The structure of the regression model is as follows:

$$y_{kt} = \beta_F F_{kt} + \alpha_t + \alpha_k + \varepsilon_{kt} \quad (1)$$

where k indexes firms, t represents time, F_{kt} is a dummy variable that matches flooding at the firm level. α_t and α_k are time and firm fixed effects respectively. y_{kt} represents different firm-level outcomes, in this case, labour productivity. If the flooding variable is significant, it will represent one of the first empirical estimates of flooding impact on Chinese manufacturing firms.

In order to reduce the possibility of omitted variable bias, which occurs when important factors that affect the dependent variable are left out, we introduce fixed effects that: (1) vary across firms but not over time (here defined as firm-fixed effects effects), (2) and/or vary over time but not across firms (time fixed effects) (Stock & Watson 2003). In this specific study, one firm-fixed effect could be the competence of management, which is unlikely to vary much over an 8-year period. The management tenure length, which is completely unobserved in the error term, may affect labour productivity (defined as revenue/number of employees), the response variable, directly by influencing the number of employees. A time-fixed effect in this study could be a health and safety regulation that influences the productivity of the firm, but does not change over the 8-year period. Controlling for such effects will reduce the standard errors of the regression, thus increasing the precision of the measure in question. By this means internal validity can be attained, meaning the statistical inferences about the causal effects of flooding on productivity are valid for the companies studied.

Labour productivity

Based on Haltiwanger *et al*. (1999), labour productivity y_{kt} is taken as:

$$y_{kt} = {}^{R}/_{E} \tag{2}$$

where R is the total revenue of a company in a year and E is the number of employees. It is an efficiency measure based on how much output each worker can produce. This is a good proxy for measuring a company's outcome because the more efficient a company is, the more output for each employee, the better the performance. Usually value added per employee is regarded as superior to revenue as a measure of output because it excludes the value of immediate inputs such as materials that are not produced by the companies, thus reflecting the marginal values that firms are creating (*Ibid*). However, data for calculating value added were not available; therefore revenue per year is used instead. In practice, revenue can be reduced when there is the cost of moving out or moving back in after a flooding event, or the cost of lost merchandise or goods.

6.4.3. Estimation

We use three model specifications based on Eq.(1). Fixed effects regressions are then run according to the different model specifications. For all models, we need to be reasonably confident that our error terms are independent of the flooding variable to avoid omitted variable bias, for instance, during a period, average flooding (regressor F) and general business cycle shocks (part of the error term) could be correlated. To control for this, we introduce time dummies by allowing for fixed effects and only exploit deviations and transform Eq.(1) into Eq.(3), shown as below.

$$y_{kt} - y_{k(t-1)} = \beta_F\left(F_{kt} - F_{k(t-1)}\right) + \alpha_t + \alpha_i + \varepsilon_{kt} - \varepsilon_{k(t-1)} \tag{3}$$

Model 1: This model focuses on firm-fixed and year-fixed effects. The null and alternative hypotheses are stated below.

H_1 (null): Flooding has **no effect** on Chinese manufacturing companies' productivity, controlling for firm- and year -fixed effects.

H_1 (alternative): Flooding has **an effect** on Chinese manufacturing companies' productivity, controlling for firm-and year-fixed effects.

Model 2: This model focuses on firm fixed and *sector year fixed effects*. These could be regulations that do not change over time for one sector, e.g. chemical controls, whereas they do change for another, e.g. mining. This is a more robust model than the first because introducing specific sector-year effects controls for more "fixed effects", whereas Model 1 only includes fixed effects that do not change over time for all companies. The null and alternative hypotheses are stated below.

H_2 (null): Flooding has **no effect** on Chinese manufacturing companies' productivity, controlling for firm and *sector year fixed effects*.

H_2 (alternative): Flooding has **an effect** on Chinese manufacturing companies' productivity, controlling for firm and *sector year fixed effects*.

Model 3: This model examines the possibility of a lagged effect of flooding, with firm-fixed and sector-year-fixed effects. The null and alternative hypotheses are stated below.

H_3 (null): Flooding has **no lagged effect** (one-year shock specified) on Chinese manufacturing companies' productivity, controlling for firm- and *sector-year fixed effects*.

H_3 (alternative): Flooding has **a *lagged* effect** (one-year shock specified) on Chinese manufacturing companies' productivity, controlling for firm- and *sector-year fixed effects*.

In addition, all three models are run on a log-linear transformation based on Eq.(3). This will make the interpretation easier, i.e. in percentage terms, if flooding is significant. The equation is

$$\log\left(y_{kt} - y_{k(t-1)}\right) = \beta_F\left(F_{kt} - F_{k(t-1)}\right) + \alpha_t + \alpha_i + \varepsilon_{kt} - \varepsilon_{k(t-1)}$$

(4)

All hypotheses are tested at a 1, 5 and 10% level of significance.

6.4.4. Robustness checks

To estimate the causal effect of flooding on companies' revenue with robustness, five key assumptions have to be met. First, the error term must have mean zero, which means that there is no omitted variable bias. To put it simply, the error term must not contain "hidden variables" that are correlated with past, present and future values of regressor F, in this case, flooding impacts in China. We control for omitted variable bias by the fixed-effects regressions. One must also assume that the error term itself is not correlated with the regressor F, which is a reasonable assumption in this case. To control for this, time dummies are introduced, because they can account for the possibility that, during a period, average flooding (regressor F) and general business cycle shocks (part of the error term) could be correlated. For example, more productive firms could systematically locate in areas with warm weather (Martin et al., 2011). These dummies will remove the correlation between flooding and business cycle shocks by exploiting deviation of productivity between one year and the next (*Ibid*).

Second, variables are independent *across* firms, but do not have to be *within* a firm. This means flooding in one firm is not to be correlated with flooding in another firm but can be correlated over time within the same firm. In simple terms, if a flood badly affects the firm this year, the effect could last into the future. To examine whether flooding impacts are correlated over time, we introduce an explicit one-year lagged effect in Model 3.

Third, there is no perfect multicollinearity, i.e. the regressors are not perfectly correlated. This is ensured because the only regressor analysed is flooding events in China.

The fourth assumption requires F_{kt} and y_{kt} to have finite fourth moments. This assumption limits the probability of drawing an observation with extremely large values of F_{it}; i.e. large outliers are unlikely. Large outliers can make OLS regression results misleading. To ensure that this assumption holds, we identify and remove the outliers.

Fifth, there must be no auto-correlation, i.e. the error terms are uncorrelated over time. However, the price of raw materials – an important factor for driving revenue growth for manufacturing companies – could be correlated over time. If the prices are high this year, they could also be high the following year. This would result in the wrong standard errors, often an underestimate because the errors are "similar" from one year to the next and no longer independent. Therefore the true deviation from the sample-mean, which is what the standard errors measure, would be "underestimated" as errors "shrink and correlate" with each other. To solve this problem, "clustered" standard errors (grouped errors that are correlated with each other) are used. This way, the errors may be correlated within the same "cluster", but not outside the clusters, and the deviation is measured more accurately.

6.5. Input-output analysis

Following the econometric analysis, we are able to estimate the firm-level labour productivity losses, which we then use to estimate sector level and ultimately macro-level economic flow losses. From the econometric models, we obtain the estimated expected annual firm-level labour productivity losses, to subsequently estimate the expected annual macroeconomic losses due to flooding.

The sectors involved in manufacturing are part of a much larger economy, which is assumed to be comprised of n interacting sectors, of which an example sector i is a part. This economy has a supply and demand balance where sectors (through firms) supply goods and services to satisfy the demands of other sectors, households and the government, and in return use resources from other sectors, households and the government to produce more. This balance is represented by the input-output Eq.(5), where the total economic output of sector i, given by x_i, goes as input towards satisfying the intermediate demands, $z_{ij}, j = \{1, \dots n\}$, of different sectors and the final demands, f_i, of households and government.

$$x_i = \sum_{j=1}^{n} z_{ij} + f_i \tag{5}$$

It is further assumed that the value of intermediate sector demand of sector i output by a sector j, z_{ij}, is proportional to the total sector j output x_j. This relationship, expressed in Eq.(6), is derived from the cost minimization under a Walras-Leontief production function (Oosterhaven 1988). Here a_{ij} is a technical coefficient whose value lies between 0 and 1.

$$z_{ij} = a_{ij} x_j \tag{6}$$

Substituting Eq.(6) into Eq.(5) produces the Leontief economic input-output model (Leontief 1988) of Eq.(7) for the supply demand equilibrium balance of the economy.

$$x_i = \sum_{j=1}^{n} a_{ij} x_j + f_i \Leftrightarrow \mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f} \tag{7}$$

Here $\mathbf{x}$ is the $n \times 1$ vector of sector outputs, $\mathbf{A}$ the $n \times n$ matrix of technical coefficients matrix, $\mathbf{f}$ the $n \times 1$ vector of exogenous demands.

The Leontief input-output model of Eq.(7) is a model of an open demand-driven economy because of the exogenous demand vector $\mathbf{f}$. To estimate direct and indirect macroeconomic losses through this model we need demand-side perturbation effects. But in the case of a disaster such flooding, supply-side perturbation effects, such as productivity losses, generally result in direct and indirect economic losses (Li et al. 2013). To represent supply side perturbations we convert the open economy Leontief input-output model into a closed economy Leontief input-output model (Steenge & Bockarjova 2007). An additional labour constraint given by Eq.(9) is introduced, where the L is a scalar of total employment, $\mathbf{l}$ is an $n \times 1$ vector of direct labour input coefficients, and $\mathbf{l}'$ is the transpose of $\mathbf{l}$.

$$L = \sum_{j=1}^{n} l_j x_j \Leftrightarrow L = \mathbf{l}'\mathbf{x} \tag{8}$$

Combining Eq.(7) and Eq.(8) and rearranging them produces the 'Basic-Equation' (Steenge and Bočkarjova, 2007), which describes a closed Leontief input-output economic model of a balanced economy. This is shown in Eq.(10), which follows from Eq.(9).

$$\begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ L \end{bmatrix} = \begin{bmatrix} \mathbf{x} \\ L \end{bmatrix} \tag{9}$$

Or

$$\mathbf{M}\mathbf{q} = \mathbf{q}$$

$$\text{Where } \mathbf{M} = \begin{bmatrix} \mathbf{A} & \mathbf{f}/L \\ \mathbf{l}' & 0 \end{bmatrix} \text{ and } \mathbf{q} = \begin{bmatrix} \mathbf{x} \\ L \end{bmatrix} \tag{10}$$

In Eq.(10) the left side, $\mathbf{Mq}$, represents the totality of inputs and the right side, $\mathbf{q}$, represents the totality of outputs (Steenge & Bockarjova 2007). The equilibrium condition

$\mathbf{Mq} = \mathbf{q}$ shows the ability of the economy to produce if the sector capacities are at levels $\mathbf{q}$ (*Ibid*).

Due to a flood disruption, we assume the production capacity of the firms is decreased, which reduces the production capacity of the economic sector. We assume the production capacity of the sector i is lost by a fraction $0 \leq \delta_i \leq 1$. Similarly the production capacity of labour is lost by $0 \leq \delta_{n+1} \leq 1$. We can construct a vector, $\widetilde{\mathbf{q}}$, of the remaining post disaster production capacity as:

$$\widetilde{\mathbf{q}} = \begin{bmatrix} 1-\delta_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1-\delta_{n+1} \end{bmatrix} \mathbf{q} = [\mathbf{I} - \mathbf{D}]\mathbf{q} \tag{11}$$

Where $\mathbf{I}$ is the $(n+1) \times (n+1)$ identity matrix, and $\mathbf{D} = \mathrm{diag}(\delta_i), \forall i = \{1, \ldots, n+1\}$.

Because of the reduced production capacities the post-disaster economy will become imbalanced and produce a reduced output given by:

$$\widehat{\mathbf{q}}^0 = \mathbf{M}\widetilde{\mathbf{q}} \neq \widetilde{\mathbf{q}} \tag{12}$$

$\widehat{\mathbf{q}}^0 = [\hat{\mathbf{x}}^0 \quad \hat{L}^0]'$ where $\hat{\mathbf{x}}^0$ is the vector-reduced economic outputs of all sectors and $\hat{L}^0$ is the reduced total labour wages in the economy after the disaster event. Eq.(12) represents the post-disruption economic outputs of an imbalanced economy, which can be treated as estimates of the initial inability of the total outputs to meet the total demands in the economy (Steenge and Bočkarjova, 2007; Koks et al. 2015). Subsequently the economy would have to readjust its circular flows to ultimately attain other equilibrium levels. We assume that the new equilibrium state is reached by readjusting final demands and total employment levels, corresponding to the reduced output levels $\hat{\mathbf{x}}^0$. This assumption is consistent with the notion that in post-disaster situations firms will prioritise intermediate demands for other sectors over final demands (Hallegatte 2008; 2014). Hence the new balanced economy is estimated by solving the Eq. (13) system of equations. We note that the value of $\hat{L}$ estimated from Eq.(13) replaces the value estimated from Eq.(12).

$$\hat{\mathbf{x}}^1 = \hat{\mathbf{x}}^0; \quad \hat{\mathbf{f}}^1 = \hat{\mathbf{x}}^1 - \mathbf{A}\hat{\mathbf{x}}^1 \;; \quad \hat{L}^1 = \mathbf{l}'\hat{\mathbf{x}}^1 \tag{13}$$

From Eq.(10) and Eq.(13) we can estimate the losses in economic outputs, $\Delta\mathbf{x} = \mathbf{x} - \hat{\mathbf{x}}^1$, final demands $\Delta\mathbf{f} = \mathbf{f} - \hat{\mathbf{f}}^1$, and labour wages $\Delta L = L - \hat{L}^1$.

In considering flood-lagged firm-level disruption effects, it is assumed that these lagged disruptions are realised after the economy is in equilibrium following the first stage of disruptions. Hence they represent a second shock on the economy whose Basic-equation presentation of Eq.(10) has outputs $\hat{\mathbf{x}}^1$, final demands $\hat{\mathbf{f}}^1$, and total employment $\hat{L}^1$. Subsequently the new equilibrium and economic losses from these disruptions are estimated by repeating the steps from Eq.(11) to Eq.(13).

The macroeconomic losses depend upon estimating the matrix $\mathbf{D}$, which is estimated from firm-level labour productivity losses of the econometric models for Eq.(1), Eq.(3) and Eq. (4). The coefficient β_F represents the average fractional loss of labour productivity, which we use as a measure of loss of production capacity. For all firms belonging to a sector i we get

$$\delta_i = (\beta_F)_i \tag{14}$$

The loss of production capacity of labour occurs due to labour deaths, which are not considered here. This means in our model $\delta_{n+1} = 0$.

Since the econometric models give us robust estimates of β_F with mean and standard error estimates, we can estimate the direct and indirect flow losses over a range of possible values to show the uncertainties in these values.

6.6. Results

6.6.1. Econometric analysis

The results for flooding impact on the logarithm of labour productivity are presented in Table 14. The total number of observations included in this analysis is 371,890. All three regression models ubiquitously show a negative impact –are all significant at the 1% level. For instance, the coefficient of the flooding variable from Model 1 is -0.0361, which can be interpreted as: flooding reduces output of "treated firms" i.e. those flooded Chinese manufacturing companies by 3.61% on average. Interestingly, the one-year lagged flooding effect, from Model 3, is also significant, standing at -0.0173. We can interpret this as an average reduction of output by 1.7% as a result of flooding lagged impacts on the those flooded Chinese manufacturing sector. This is not surprising because one would expect the negative flooding impacts from destroying capital and/or labour to fade as reconstruction commences.

The adjusted R-squared is a modified version of R-squared, which is a statistical measure of how close the data are to the fitted regression line. Normally the higher the value of R-squared, the better the fit. However, R-squared tends to increase just as we add more explanatory variables even though those variables might not be good explanatory variables. The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. The adjusted R-squared increases only if the new term improves the model more than would be expected by chance. In our case, it varies between 0.011 and 0.020, which seems low. However, this does not change the fact that the flooding variable has a statistical effect on firms, although it does mean that it has limited explanatory power in the variation of labour productivity in firms. This is not surprising given that company labour productivity is influenced by many factors such as technology and economic conditions at the time. It increases marginally from 0.011 in Model 1 to 0.020 in Model 3, indicating that by including sector-year-fixed effects, we are controlling for more information that has been constant over time than if we simply used the year-fixed effects, which apply to all companies.

Table 14. Results for the impact of flooding on the logarithm of labour productivity

	Model (1)	Model (2)	Model (3)
Variables	Logarithm of Labour productivity		
Flood	-0.0361***	-0.0318***	-0.0387***
	(0.00825)	(0.00836)	(0.00900)
Flood_lagged			-0.0173**
			(0.00664)
Constant	-0.412***	-0.306***	-0.276***
	(0.0913)	(0.0430)	(0.0451)
N	371890	371890	371890
Adj. R-sq	0.011	0.020	0.020

Notes: These regressions were estimated using panel data for major flooding events in China on 162,830 Chinese manufacturing companies between 2003 and 2010. Model (1) focuses on firm fixed and year fixed effects; model (2) focuses on firm fixed and *sector—year-fixed* effects; model (3) examines the possibility of a lagged effect of flooding. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.6.2. Macroeconomic analysis

For the macroeconomic analysis, we have taken the 2010 IO accounts of the Chinese economy. In these IO accounts the Chinese economy is disaggregated into 41 sectors (listed in Appendix 8), from which we are able to build the Basic Equation model Eq.(10).

Out of these, 16 sectors, from numbers 6-21, are the manufacturing-based sectors to which our 162,830 companies belong. We assume that these 162,830 companies exhaustively make up the whole of the manufacturing sector, which means they cover all production of the 16 manufacturing-based sectors in the IO accounts.

As the econometric analysis of Model 1 shows, flooded manufacturing-based firms suffer an average labour productivity loss of $\bar{\beta}_F = 3.61\%$ due to the disaster. This for us implies that the firm capacities and correspondingly the production capacity of all manufacturing-based sectors declines by 3.61%, i.e., $\delta_i = 0.0361, \forall i = \{6, \dots, 21\}$. We assume all sectors which are not manufacturing-based do not suffer any capacity reductions, i.e., $\delta_i = 0, \forall i \neq \{6, \dots, 21\}$. A similar process is followed in estimating macroeconomic losses from Model 2 where $\delta_i = 0.0318, \forall i = \{6, \dots, 21\}$. For Model 3 again the same process applies, with $\delta_i = 0.0387, \forall i = \{6, \dots, 21\}$.

With the above assumptions, we are able to construct the $\mathbf{D}$ matrix and obtain the reduced post-disaster production capacities $\widetilde{\mathbf{q}}$ from Eq.(11). This allows us to find the new economic equilibrium, which gives the reduced economic outputs ($\hat{\mathbf{x}}^1$), exogenous demands ($\hat{\mathbf{f}}^1$), and labour wages ($\hat{L}^1$) from Eq.(12) and Eq.(13). Subsequently we can find the loss of outputs, demands and labour wages. These losses are reported as the annual losses for the Model 1, Model 2, and Model 3 estimates of labour productivity losses. These losses are estimated for the average and the standard error ranges at 1% and 99% confidence intervals of $\beta_{\mathbf{F}}$ estimates.

For Model 3 we have flood-lagged effects due to which there are further macroeconomic losses over the next year. Assuming the same 2010 IO structure, we take the new Model 3 equilibrium at the end of year one and repeat the whole process above with $\delta_i = 0.0179, \forall i = \{6, \dots, 21\}$ corresponding a $\bar{\beta}_F = 1.79\%$ decline in labour productivity due to flood lagged effects. Again the losses are estimates for the average and the standard error ranges at 1% and 99% confidence intervals of values.

Table 15 shows the mean and standard error results for the three models, with initial, lagged and cumulative estimates for Model 3. For all three models there are substantial losses for the Chinese economy, highlighting the importance of the manufacturing sectors. We see that overall, due to 3.18% to 3.87% mean reductions in labour productivity of the sectors involved in manufacturing, the Chinese economy suffers a 1.38% to 1.68% mean losses in total direct and indirect outputs, which amounts to 17,323 to 21,082 RMB billion.

Since economic outputs are reduced there is an effect on the total labour wages, which suffer mean losses of 1.17% to 1.43% or 2,545 to 2,728 RMB billion. As a result, the overall demand for sector outputs also reduces, which is seen in terms of mean losses of demand of 1.24% to 1.51% or 5,024 to 6,114 RMB billion. For Model 3 there are further lagged losses, resulting in cumulative losses over 2 years. For instance, Model 3 results show 2.43% or 30,307 RMB billion mean total sector output losses over 2 years. The wide ranges in these values show the profound influence of manufacturing-firm-level disruptions on the overall economy.

Table 15. Results for the overall annual IO macroeconomic losses for the 2010 Chinese 41- sector economy.

	Model 1	Model 2	Model 3		
			Initial	Lagged	Cumulative
% losses					
Total Sector Outputs	1.57(0.36)	1.38(0.36)	1.68(0.39)	0.75(0.29)	2.43(0.68)
Total Exogenous Demands	1.41(0.32)	1.24(0.33)	1.51(0.33)	0.67(0.24)	2.19(0.57)
Total Labour Wages	1.33(0.30)	1.17(0.31)	1.43(0.35)	0.64(0.26)	2.06(0.61)
Loss Values (RMB billions)					
Total Sector Outputs	19666(4494)	17323(4554)	21082(4903)	9225(3477)	30307(8379)
Total Exogenous Demands	5703(1303)	5024(1321)	6114(1422)	2677(1009)	8791(2431)
Total Labour Wages	2545(582)	2242(589)	2728(634)	1196(451)	3924(1086)

*The results are shown as percentages and magnitudes of losses in total sector outputs, exogenous demands and total labour wages. Standard error values are in brackets.

Through the IO analysis we can break down the economic losses into sector specific estimates. These provide more clarity in breaking down the direct and indirect impacts on the economy. We discuss these results only for Model 3 analysis here, as the Model 1 and Model 2 results for 1-year annual losses show similar trends. In Figure 28 the bar plots show the values of sector output losses $\Delta\mathbf{x} = \mathbf{x} - \hat{\mathbf{x}}^1$ along with the standard error estimates, in terms of magnitudes in RMB billions. The manufacturing and non-manufacturing sectors have been separately highlighted to show that the IO loss effects cascade beyond manufacturing sectors to the rest of the economy. While the results for the manufacturing sector show the combined direct and indirect flow losses, for all other sectors these are purely indirect flow losses. We observe that industries such as chemical and metal smelting and rolling processing suffer the highest losses at 2,690 and 2,693 billion respectively. There are also substantial economic output losses incurred by the non-manufacturing sectors such as agriculture (1,542 RMB billions), oil and gas (733 RMB billions), and key infrastructure sectors such as electricity (626 RMB billions) and transport (660 RMB billions). Overall, service industries tend to be less affected. In addition, the lagged losses after one year are significant. This is especially the case for non-manufacturing sectors – agriculture (678 RMB billions), oil and gas (321 RMB billions), metal mining (282 RMB billions), electricity (309 RMB billions), transport (289 RMB billions), and the wholesale and retail (253 RMB billions) industries.

In Figure 29 the bar plots show the sector-specific percentage output losses for 2 years. We observe that in terms of percentages, the losses are more evenly spread out across all sectors, with oil and gas and metals mining sectors suffering the highest losses. The lagged losses after a year of flooding events are much higher for most sectors, are particularly prevalent in oil and gas, metal mining, and are consistently high for all manufacturing sectors.

Comparatively Figures 28 and 29 also highlight the differences in the indirect losses when assessed in absolute terms and percentages respectively. In particular, we see that in terms of absolute magnitudes the manufacturing-based sectors incur the highest losses, which is as expected. But in percentage terms the oil and gas and metals mining sectors suffer much higher impacts, which show that the indirect flow losses are relatively more severe for non-manufacturing sectors. This distinction could be crucial in disaster recovery planning.

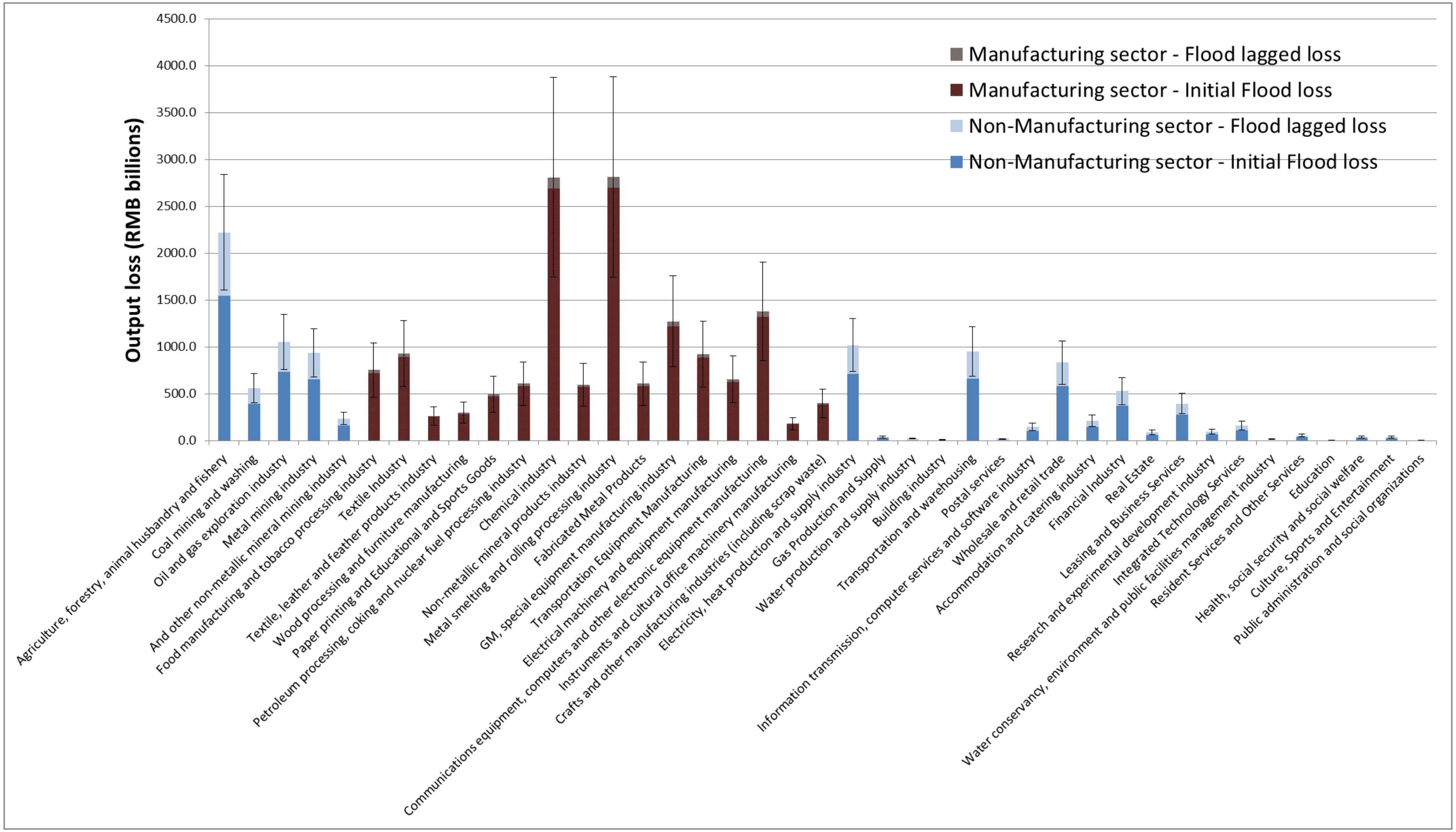


Figure 28. Model 3 results for sector-specific mean and standard error economic output losses for the 41-sector Chinese IO economy.

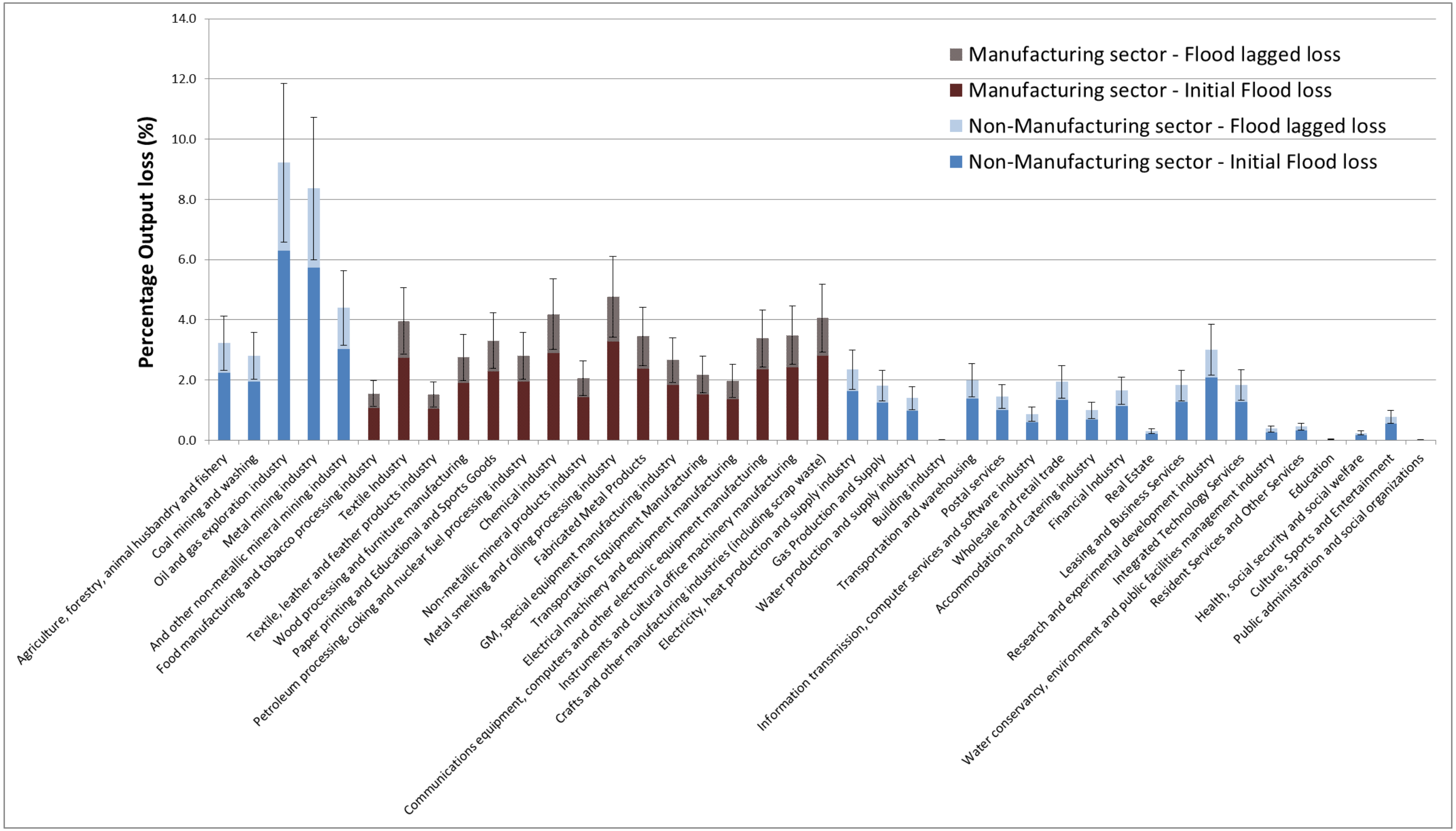


Figure 29. Model 3 results showing the sector specific mean and standard error percentage output losses for 2 years for the 41 sector Chinese economy.

6.7. Discussion and conclusion

The objective of our paper is to present a demonstrable methodology to quantify the economic consequences of disruption to manufacturing firms due to flooding and the associated systemic propagating indirect effects on the national economy. We have combined detailed firm-level econometric analysis with a macroeconomic input-output model to provide a data-driven approach. From the econometric analysis of manufacturing-based firms in China, we found that flooding on average reduces affected manufacturing firm output by 3.18%-3.87% per year depending upon considerations for firm-, time- and sector-level fixed effects. Assuming these firm-level output reductions are systemic across the manufacturing sector, we quantify their propagating effects on the Chinese macroeconomic system via a supply-side driven IO impact assessment model. Our analysis shows that there is a 1.38% - 1.68% annual loss in total direct and indirect output, which amounts to (17,323 – 21,082) RMB billions. We also consider flood lagged effects over the next year and find that there are further 1.73% at the firm level and 0.75% or 9,225 RMB billion of total direct and indirect losses in the Chinese economy at the macro-level. Estimates for losses in labour wages and final demands are also reported. Further, our analysis captures the uncertainties in the econometric and macroeconomic measures.

In terms of economic sectors, we observe that within the whole Chinese manufacturing sector, industries such as chemical and metal smelting and rolling processing suffer the highest losses at 2,690 and 2,693 billion respectively. As for the non-manufacturing sectors, we observe significant indirect impacts on agriculture, oil and gas, and key infrastructure sectors such as the electricity, heat production and supply industry, the gas production and supply, the water production and supply industry, the building industry, the transportation and warehousing industry, the information transmission, computer services and software industry.

Magnitude-wise we see that agriculture, oil and gas, electricity and transport sectors incur more severe losses than most manufacturing sectors. In absolute percentages, we observe that indirect losses are more widespread across the economy with the oil and gas and mining sectors incurring greater percentage losses than manufacturing sectors. Such results highlight the interconnected nature of the economy and the importance of the manufacturing sectors to the outputs of other sectors. Further significant lagged losses are observed for the whole economic system.

To our knowledge, this is one of the first studies ever that provides an empirical estimate of flooding impacts at the detailed spatial granularity of firm levels for China. It is also a novel attempt to link firm-level results with macroeconomic analysis to estimate natural disaster impacts in China. We demonstrate how the interdependency of different sectors could result in losses from one sector to the next and provide evidence as to which sector might be affected the most. Thus, an important implication of our work is that simply being located in areas where there have been large floods could have a significant cost for firms, not only those in the affected regions but also much more broadly. As such, it is crucial for us to study how sectors and ultimately firms are related, for instance, the supply chain and the spatial interrelationships of sectors and firms.

In addition, our work demonstrates that interdependency is not only linked with sectors, but also with time. Many business analysts believe the impact of flooding on manufacturing companies is short-lived and that they normally bounce back post the event. We hereby provide contrary evidence that post disaster, the financial losses for firms can still be significant.

There are several limitations to this study. One is that we present an average effect of treated firms i.e. those affected by floods, but firm characteristics differ, which means that the "true" cost for an individual business might be larger or smaller depending on its size and that of the sector, which we do not examine. In effect, the "true" cost on individual businesses depends on many factors such as their supply chain; their adaptive capacity, including their capacity to plan for emergency responses; and the size and exogenous factors such as the availability of government assistance among others. Another limitation of this study is the resolution of the floods, which is at city scale. It would be preferable to use the actual extent of floods to improve the precision of the geo-location of affected firms. In addition, this is only a partial review of flood impacts, as we focus on the manufacturing sector and propagating effects on the broader economy; there would have been impacts on other sectors as well as households. Further, we are not able to incorporate the costs of capital replacement, reconstruction and replacement of damaged stocks as our measure of firm output is based on an index of revenue and labour. Inclusion of such estimates is not possible due to a lack of data availability.

Overall, this research calls for a more comprehensive assessment of flooding impacts at firm level and their propagating macroeconomic effects. This is because firms ultimately bear the business costs of extreme weather events yet we do not understand how they are affected, nor do we understand how other sectors may be impacted owing to the interconnectivity of the economy. Further work could apply more nuanced IO and GCE models which capture firm and household responses, although the limited availability of data currently prohibits us from conducting such work.

7. Variability of flood exposure in China's infrastructure systems in the context of a changing climate

7.1. Summary

A warmer climate is expected to increase the risks of floods in the majority of river basins and coastal floodplains globally (IPCC 2007; IPCC 2012a; Hirabayashi et al. 2013). China is one of the hotspots of flood impacts where associated human and material losses are heavily concentrated (IPCC 2014; Hu et al. 2015). Using the daily runoff of eleven Atmospheric and Oceanic General Circulation Models (AOGCMs), we apply and downscale a global river routing (CaMa-Flood) model to assess how flooding probabilities will change in China under different warming scenarios. We find that as we progress into the future, flooding extent generally increases for both RCP 4.5 and 8.5. Interestingly, most of the flooding would be caused by lower return period events rather than higher return period events, which tend to receive more attention in the press. In addition, there is much spatial variation depending on the climate model, return period and time period concerned. In the worst case scenario for instance, we show that flooding concentrates in Anhui, all of Jiangsu, northern Shandong and western Heilongjiang for RCP4.5 between the baseline period 1986–2005 and the period 2016–2035. By 2055, the probability of flooding increase extends along the Yangtze River provinces (Hubei, Hunan, northern Jiangxi) as well as to other regions in the north.

A substantial impact from flooding is the damage to infrastructure systems, which can result in huge economic losses that can extend beyond the flooded area. Despite the key role they play, little is known about the extent to which Chinese infrastructure systems are exposed to climate impacts. Here we apply the global CaMa-Flood model to a new network-based infrastructure database for China, covering a total of 60,916 assets including the energy, water, transport, waste and digital communication sectors. Our analysis shows that by 2055, the percentage of infrastructure assets exposed to increasing probability of flooding under RCP 4.5 are 28%, 29%, 30%, 22%, 20%, 44%, 14% for airports, dams, data centres, ports, power plants, rail stations, reservoirs respectively. The

percentage of line assets exposed to increasing flood hazards are 20%, 22%, 23% and 26% for oil pipelines, rail tracks, roads and transmission lines respectively. Under RCP 8.5, the percentages are 35%, 32%, 36%, 30%, 22%, 43%, 13% for aforementioned point assets. Linear asset percentages are 28%, 37%, 28% and 32% for the assets mentioned above. These percentages indicate that overall that across all sectors, a substantial number of assets will be exposed to increased flooding. Further, we demonstrate that the importance of considering regional variation for understanding flooding exposure. We find that central south, east, northeast and north in China have more oil pipelines facing increasing flooding hazard whereas northwest and southwest have less. For reservoirs, north and northeast have more assets under threat compared to the other regions.

Lastly, from the direct flood exposure analysis of assets, we infer the indirect exposure of customers reliant on those infrastructure assets within and outside the floodplain which could be also high. The average number of customers affected by increasing flood probabilities are 54 million, 114 million and 131 million for airports, power plants and stations respectively. Overall this analysis shows the importance of considering the detailed/finer spatial variation of flooding an infrastructure sectors in determining changing flood exposure due to climate change. Such an understanding will be key for national and regional infrastructure planners in prioritising infrastructure resilience investments contingent on likely climate change impacts.

7.2. Main

There is increasing evidence that suggests floods, among other extreme weather events, are expected to intensify in a changing climate (Alfieri et al. 2015; Schaller et al. 2016). If unmanaged, these could significantly damage and affect the performance of infrastructure assets and networks. Generally, such infrastructures are large-scale physical systems that are built to last for many years, and once built they lock in patterns of development over several decades (J. W. Hall et al. 2016).

China has been the world's largest infrastructure investor since 2013 (Dobbs et al. 2013) and used more concrete in 3 years (2011–2013) than the U.S. used in the entire 20th century (Swanson 2015). China's new infrastructure has been frequently hit by floods. In 2014, due to flooding events, 62 rail links and 33,569 roads were disrupted (compared to 28 and 21,961 respectively in 2011), in addition to the failure of 14,316 electricity transmission lines (compared to 8,516 in 2011), prompting the shutdowns of factories and cutting off power to millions of households (Ministry of Water Resources 2014a; Ministry of Water Resources 2011b). This year (2017), China experienced a historically unprecedented flood year with a total of 44 rivers and 74 stations under "yellow or red" alert in the Yangtze River basin alone (Song 2017). The Three Gorges Dam, the world's largest power plant by installed capacity, reduced its output from 18.12 million kw to 6 million kw, a decrease of 66.9%, due to flooding on the Yangtze river in July, shutting down 19 units out of 28 (Zhang 2017).

Although there have been studies of infrastructure vulnerability to extreme weather events (Pant et al. 2016; Thacker, Pant, et al. 2017; Arvidsson et al. 2015), few have taken climate change into account and adopted a national-scale perspective. Here, we demonstrate the exposure of China's infrastructure assets and networks to changing climate risks, using flooding as an example of intensifying extreme weather events. This is important not only because of the significant existing infrastructure stock that China possesses that could be exposed to increasing flooding risks, but also as China's ambitious "going abroad strategy" materializes, which could see Chinese approaches to infrastructure development being adopted in many developing nations.

We assemble and create a unique geospatial network-based database that contains a total number of 60,916 infrastructure assets (Hu *et al.*, 2014; Hu *et al.*, 2015) for China, in the energy, transport, water, waste and digital communication sectors with their associated range of design protection standards (see supplementary Table 17). For most sectors, this database contains the large majority of the existing infrastructure assets and networks in China, covering eleven types of individual assets, including airports, dams, data centres, ports, power plants, rail stations, reservoirs, oil pipes, rail tracks, roads and transmission lines. Contingent on data availability, infrastructure use by customers of some of the sectors is also assembled. Where the sector data are not as extensive, the assets that are responsible for satisfying most of the customer demands and are considered the most important are included.

To understand climate-change-driven flooding, inundation maps for China are prepared at 0.25° x 0.25° grid cell resolutions by running a global river routing model – Catchment-Based Macro-scale Floodplain (CaMa-Flood) – using the daily runoff of 11 Atmospheric and Oceanic General Circulation Models (AOGCMs) (Yamazaki et al. 2011). The model is validated in China with historical records of flooding (Hirabayashi et al. 2013). Average flood fractions (0 to 1.0) over 20 years for each AOGCM for all flood events of return periods greater than 1 in 30 years, 1 in 50 years and 1 in 100 years are extracted for representative concentration pathways RCP4.5 and RCP8.5 respectively. We selected these return periods because the flood protection standard for Chinese infrastructures typically ranges between 1 in 10 years to 1 in 100 years, as required by the law released by 2015. Given most assets were built before this, it is reasonable to assume the standards were designed at least within this range if not lower.

We calculate the area in square kilometres for each AOGCM for the periods of 2016–2035 and 2036–2055 (Supplementary Information Figure 37). In general, as we progress into the future, the flooding extent increases. For the 30-year return period or greater, the range of flooded area in China is between 24,649–75,363 km^2 and 25,494–76,379 km^2 at RCP4.5 and RCP8.5, respectively. This is an approximate range of area equivalent to Wales (on the lower end) and Scotland (on the higher end). With regard to return period 50 or more, the range is 14,037–49,805 km^2 and 15,468–52,892 km^2 at RCP4.5 and RCP8.5, respectively. Similarly, for return period 100 or more, the range is between 7,177–28,326 km^2 and 6,973 –34,754 km^2 at RCP4.5 and RCP8.5, respectively. These results show that most of the flooding would be caused by lower return period events.

While overall flooding might increase in area, there will be wide spatial variations in the patterns of changing flood extents, which varies significantly depending on the climate model, RCP, return period and time period concerned. In some areas, the flood fractions will increase, while others will witness decreasing or no changes in flood fractions. To demonstrate such spatial variability, we calculate the **net change (difference between increasing flood exposure areas and decreasing flood exposure areas)** in flooded areas for all AOCGMs between period 1 (2016–2035) and period 2 (2036–2055), in comparison to a baseline period 1986–2005 (Figure 30). We observe that the net change in flooded area is almost always positive in all models, which indicates that China will face an overall increasing probability of flooding in the future. A higher RCP generally leads to higher flooding extent; however, this varies notably between models.

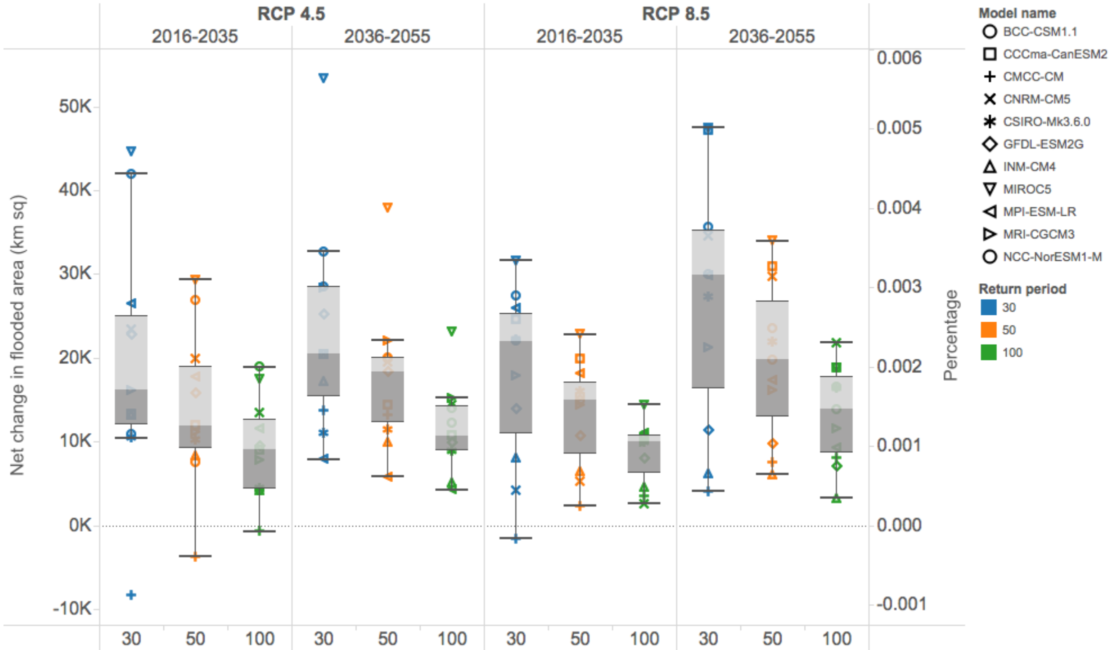


Figure 30. Projected net change in flood area (km2) in China for all AOCGMs given different return periods and radiative forcing assumptions.

Net change in flooded area for each return period (and greater) broken down by time period and RCP. Colour (blue, orange and green) shows details of return period. Blue indicates return period of 30 or greater; orange indicates return period 50 or greater; green indicates return period 100 or greater. Shape shows details of AOGCM model name. There are two future time periods: period 1 (difference between 1986–2005 and 2016–2035) and period 2 (difference between 1986–2005 and 2036–2055). Overall, there are 132 model variations depending on the return period, the time period, RCP and AOGCM model assumptions.

The spatial variation is extremely important for planning climate resilient infrastructure as exposure of infrastructures to natural hazards is highly location-sensitive. To demonstrate this, we select power plants from the infrastructure database and superimpose changing flooding hazard maps for return period > 50, varying RCP and time period for model MPI-ESM-LR (Figure 31). This model appeared the most frequently in the medium range of all models in Figure 30 (medium for bars 1-12), which arguably represents a reasonable scenario of flooding extent in the future periods concerned.

We observe that flood hazards for RCP 4.5 are concentrated along the Yangtze River (Figure 31a), in southern Hubei, northern Hunan, central Anhui, northern Jiangxi and Shanghai. Provinces such as Guangxi, Guizhou and Ningxia face wide-spread increasing flood hazard whereas Shaanxi (north), Shandong (northwest), Qinghai (central-north), Heilongjiang (east), Tibet (central) experience regional specific flood hazard. By 2055, flooding hazard escalate in large parts of Tibet and Xinjiang, Inner Mongolia. Notably the areas along the Yangtze River are no longer facing increasing hazard (Figure 31c). For RCP8.5, concentrations of increasing flooding probability are similar to RCP4.5 during the period 2016-2035, along the Yangtze River. Notable differences are in regions such as northern Heilongjiang and northern Inner Mongolia, which suffer increasing flood hazard whereas they do not in RCP4.5. By 2055, hazards become widespread with very few areas left intact.

Decreasing flood hazard, on the other hand, is less in extent in general. For RCP 4.5, most are concentrated in Hebei, eastern Sichuan and central Jiangsu, eastern Inner Mongolia. By 2055, the overall number of areas facing decreasing probability of flooding declines. For RCP 8.5, it is a similar pattern compared to RCP 4.5.

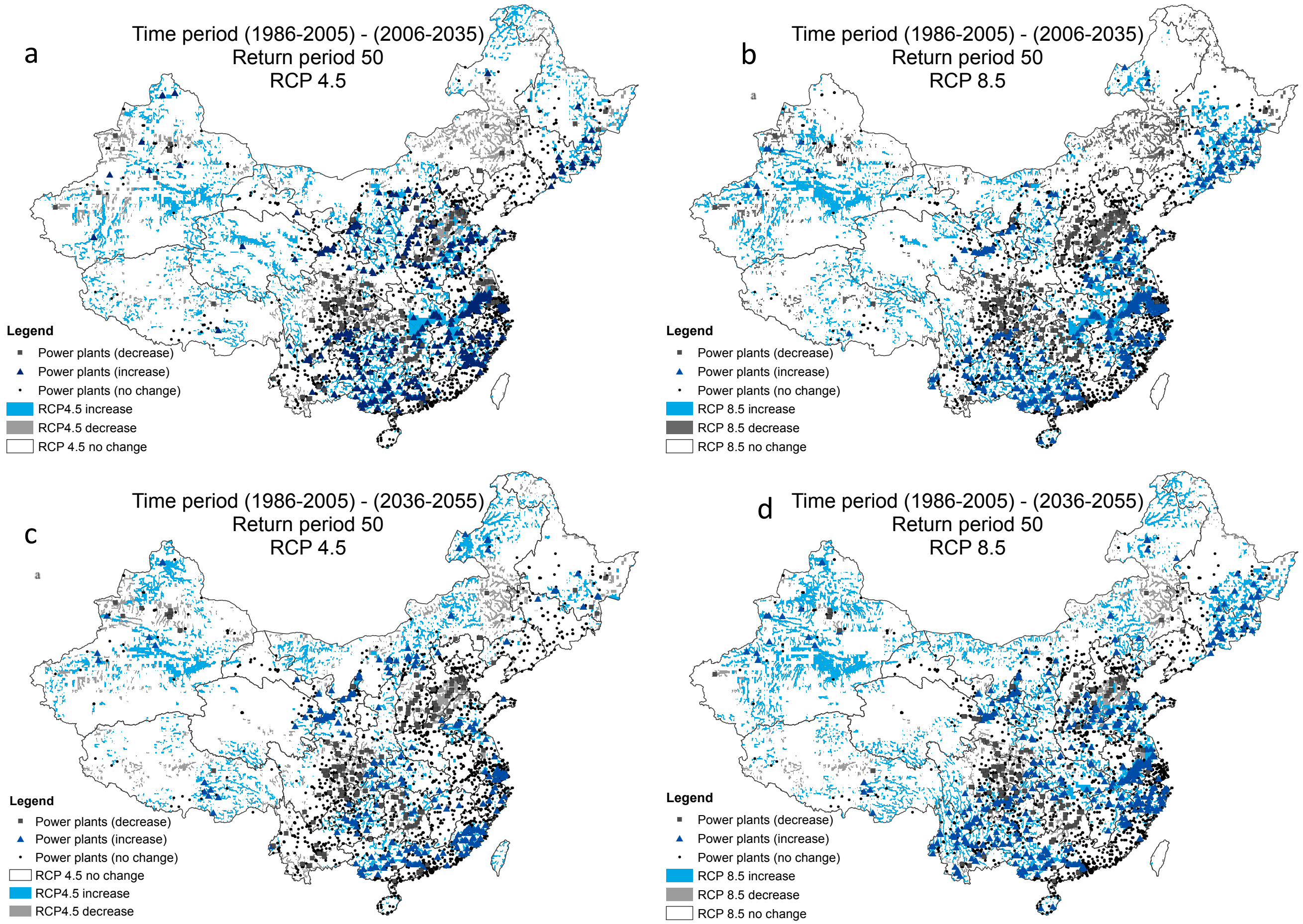


Figure 31. Locations of power plants exposed to changing (increasing, decreasing, non-changing) flood hazard for model MPI-ESM-LR.

Squares are power plants facing decreasing flood hazard; triangles are power plants facing increasing flood hazards; circles are power plants facing non-changing flood hazards. All figures are for return periods greater than 50, but we vary RCP (4.5 in Figures 31a and 31c; 8.5 in Figures 31b and 31d). Time period (1986–2005) to (2006–2035) is shown in Figures 31a and 31b whereas time period (1986–2005) to (2036–2055) is shown in Figures 31c and 31d.

We also show the spatial variation of flooding extent from model MIROC5, which appeared the most frequently in the maximum range of all models in Figure 30 (maximum for bars 1-12). This provides us with an idea of some of the worst scenarios of climate-induced flooding for China in the future (Supplementary Information Figure 38). In contrast to model MPI-ESM-LR, MIROC5 shows flooding concentrates in Anhui, all of Jiangsu, northern Shandong and western Heilongjiang for RCP4.5 between the baseline and the period 2016–2035. By 2055, the probability of flooding increase extends along the Yangtze River provinces (Hubei, Hunan, northern Jiangxi) as well as to other regions in the north. For RCP8.5, the regions exposed to increasing flood hazard again vary significantly, mostly in parts of Hebei, southwest Heilongjiang, Shanghai and central Tibet. By 2055, the flooding extent is similar to RCP4.5 given by model MPI-ESM-LR. What we demonstrate here is the importance of considering the spatial variation of changing risks which depend on the assumption of RCP, the time period and the model concerned.

This spatial variation in flooding extent given the different scenarios means that the same infrastructure stock can be exposed to distinctively changing increasing, decreasing or non-changing flood probabilities. Figures 31a and 31c demonstrate that the power plants (blue triangle) located in southern provinces will face increasing probability of flooding during 2016-2035, yet other power plants in southern Jiangsu, among others, which did not initially face any increasing risks, will be exposed to flooding by 2055. For RCP 8.5, the variation is significant. Many power plants in Sichuan for example, will face increasing flood hazard as compared to the earlier period of 2016–2035. For the RCP 4.5 in the worst scenario (Supplementary Information Figure 38), the power plants exposed are mostly near Shanghai, in Jiangsu, Anhui, Zhejiang provinces in the first period. By 2055, the locations of power plants facing increasing flood probabilities extend to central China.

To examine further how infrastructures are exposed to changing flooding hazard, we calculate the net percentage change (see methodology) of all infrastructure assets and networks in the database that are exposed to changing probability of flooding for RCP 4.5 and 8.5 in both time periods separately (Figures 32-34). A positive net change indicates the proportion of all assets facing increasing probability of flooding. Similarly, a negative and zero net change indicates the proportion of assets facing decreasing or non-changing flood hazard.

For point assets (airports, dams, data centres, ports, power plants, rail stations, reservoirs), we observe that overall, more assets will face an increasing rather than decreasing probability of flooding, as the majority of models show (Figure 32). The exception is model CMCC-CM, which shows that most assets, apart from reservoirs, will face decreasing hazard – although it would seem that as we increase the return period, the percentage of assets facing increasing flood hazard decreases. However, it is of surprise to us how small the decrease is. In other words, regardless of the return period, a good percentage of assets will face an increasing probability of flooding.

In terms of individual asset sector, power plants, rail stations, airports and ports are most exposed. For power plants between 2016-2035, the range of assets exposed to increasing probability of flooding is [-9%–26%], [-8%–9%], [-3%–18%] for RCP4.5 and for return periods greater than 30, 50 and 100 respectively. Between 2036-2055, the range is [-8%–30%], [-2%–26%], [2%–17%], a ubiquitous increase as we progress into the future. For RCP8.5, the range of assets exposed to increasing flood hazard is [-16%–19%], [-8%–15%], [-5%–12%] for return periods greater than 30, 50 and 100 respectively. Between 2036 and 2055, the range is [-3%–27%], [0%–20%], [2%–15%]. The ranges of net change for other sectors (rail, airports, ports) are somewhat similar, except for return periods greater than 30 between 2036–2055, when they increase significantly to more than 30% for most models.

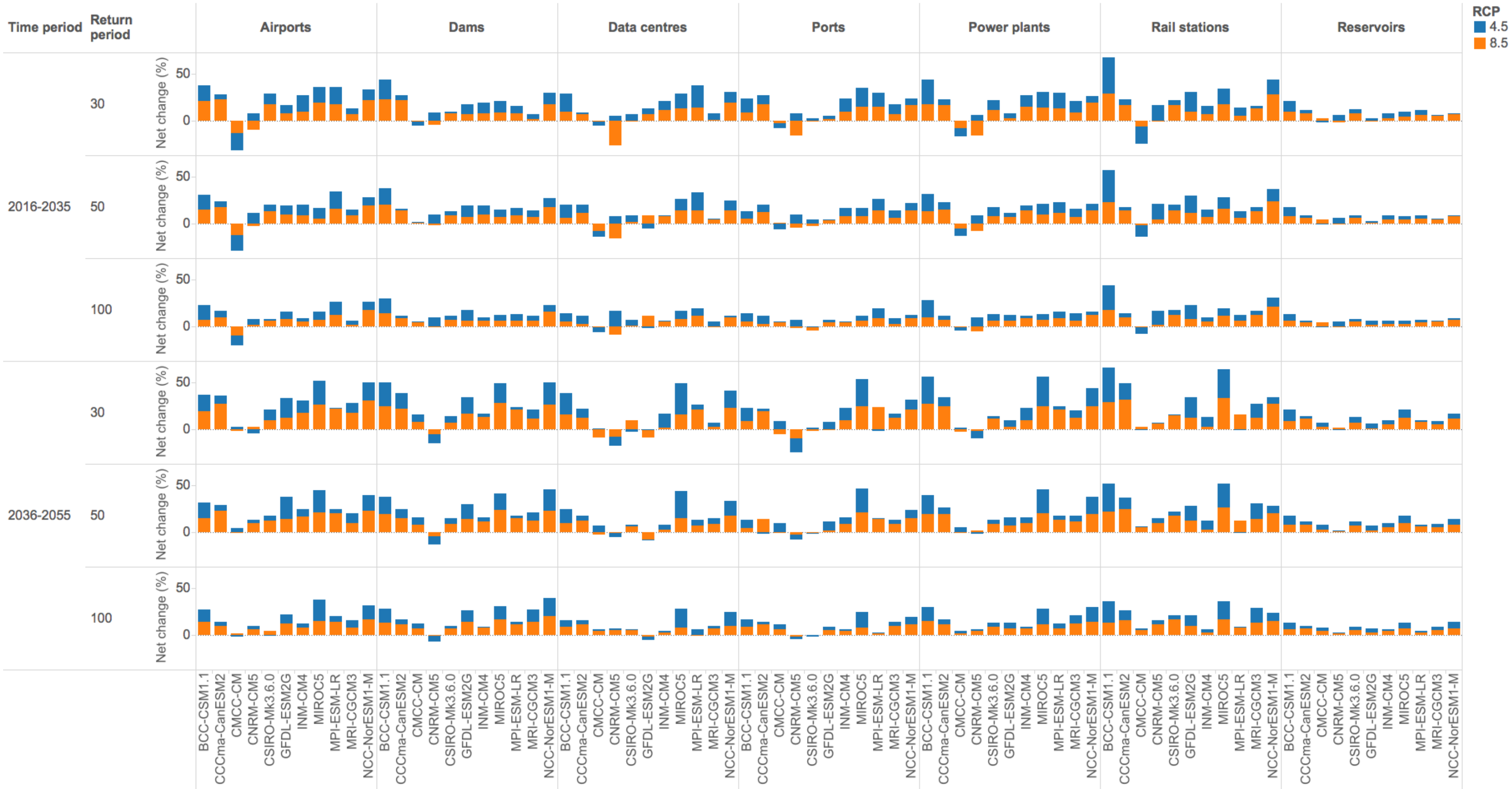


Figure 32. infrastructure point assets (power plants, rail stations, ports, airports, reservoirs, dams, data centres) exposure to percentage net change (positive, zero or negative) of flood hazards for all models at return periods greater than 1 in 30, 1 in 50 and 1 in 100 years. Two time periods are shown: (1986–2005) to (2006–2035) and (1986–2005) to (2036–2055).

For linear assets (Figure 33), as with point assets, we observe that most experience increasing probability of flooding. Interestingly, the range of percentages for linear assets exposed to changing flood hazard is very similar for all sectors, as compared to the point assets, which is possibly a reflection of the fact that line assets are more equally spread out across the hazard areas whereas point assets are concentrated in particular urban hazard areas (along the coast and in central China). In terms of absolute length exposed, for oil pipelines between 2016-2035, the range of assets exposed to increasing flood probability is 6,009–16,309 km, 4,333–14,517 km, 2,561–10,954 km for RCP4.5 and for return periods greater than 30, 50 and 100 respectively. For other linear assets, the length range is similar. To put that in perspective, this is the approximate equivalent of the distance between New York and Dallas in Texas for the smaller range of distance (2,561 km) and New York and New Delhi for the highest range (10,954 km).

We further analyse the number of customers indirectly affected by the changing probability of flooding, measured by net change. This estimates the number of customers dependent on those infrastructure assets that face increasing flood hazard minus the customers dependent on those assets that face decreasing flood hazard (Figure 34). We use a set of customer allocation models and apply these on existing infrastructure stock in China (see methodology) (Hu et al. 2015). The net change in absolute terms for customers shows more interesting variation compared to net percentage change for the individual assets. Overall, there are more customers affected by exposure to power plants and rail stations than airports. The average number of customers affected by net increasing hazard are 54 million, 114 million and 131 million for airports, power plants and stations respectively. Not many models show decreasing exposure to flood hazard for customers, except for models CMCC-CM and CNRM-CM5.

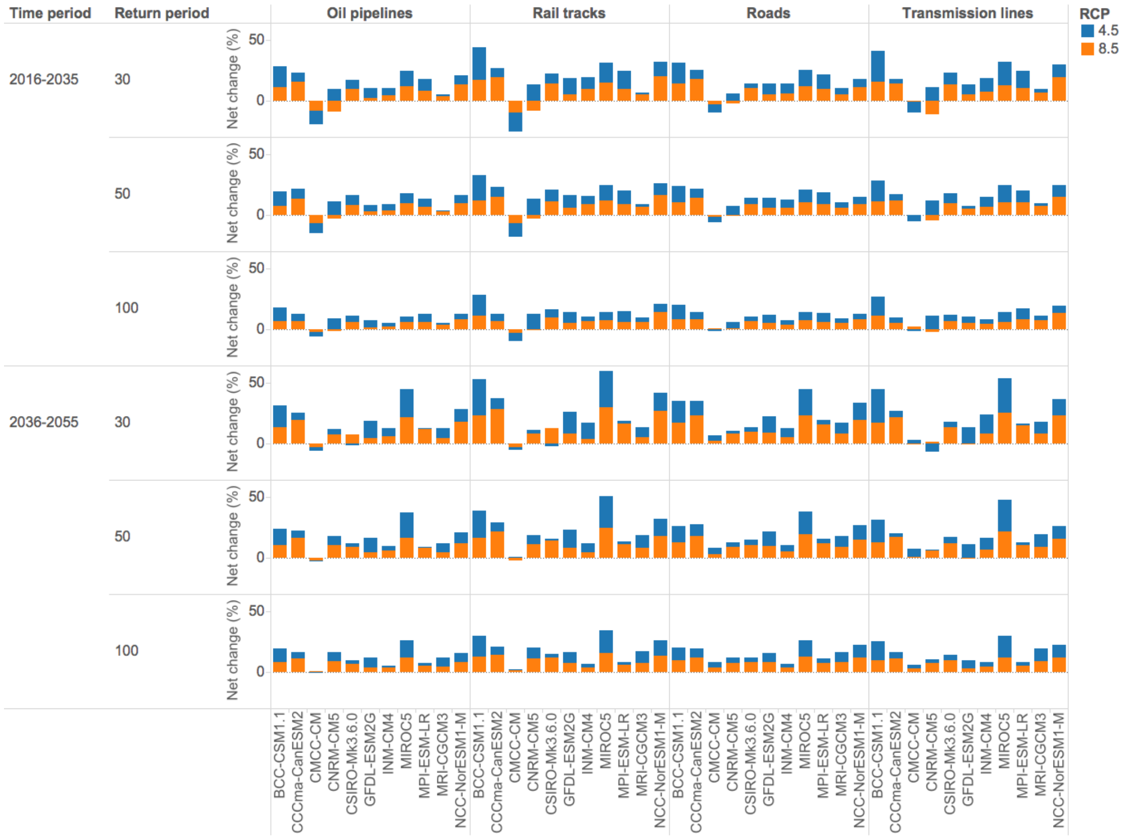


Figure 33. Infrastructure line assets (oil pipelines, rail tracks, roads, transmission lines) exposure to percentage net change (positive, zero or negative) of flood hazards for all models at return periods greater than 1 in 30, 1 in 50 and 1 in 100 years. Two time periods are shown: (1986–2005) to (2006–2035) and (1986–2005) to (2036–2055).

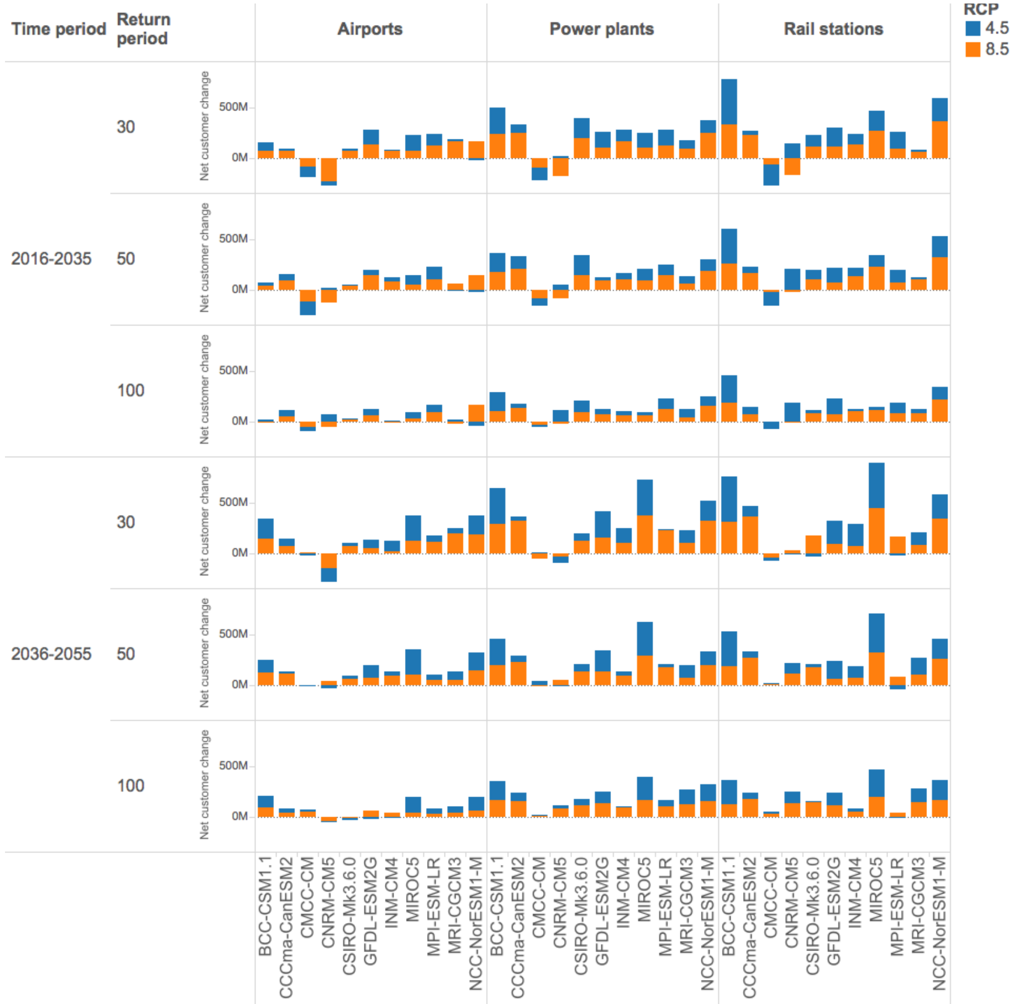


Figure 34. Net change in customer (in absolute terms) exposure for airports, power plants and rail stations for all models at return periods greater than 1 in 30, 1 in 50 and 1 in 100 years. Two time periods are shown: (1986-2005) to (2006—2035) and (1986-2005) to (2036—2055).

The above analysis is done at an aggregate level. We next look into the regional variation of changing flooding hazards for infrastructure assets and networks in China. We divide China into seven regions: central south, east, north, northeast, northwest, southwest, Hongkong, Macau and Taiwan (Figure 35; Supplementary Information Table 18). We do not show the regions including Hongkong, Macau and Taiwan because there are no data. We observe, in Figure 36, that regional variation is significant for certain assets such as data centres, ports, oil pipelines and reservoirs. Central south, east, northeast and north have more oil pipelines facing increasing hazard whereas northwest and southwest have less. For ports, it is another story. For reservoirs, north and northeast have more assets under threat compared to the other regions.

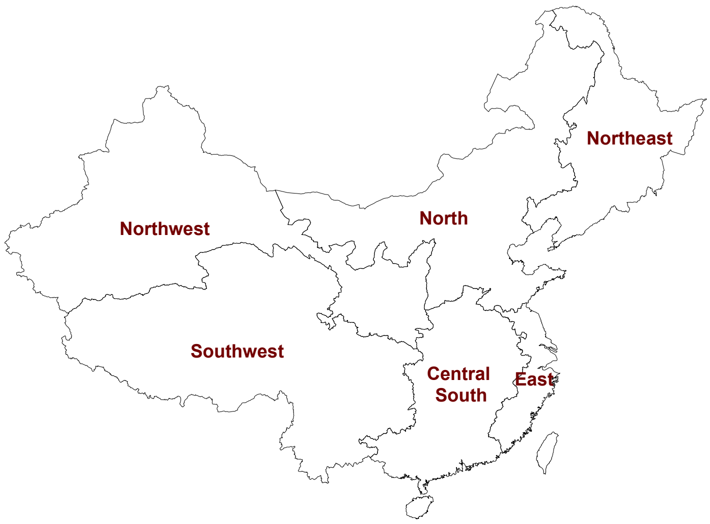


Figure 35. Regional division of China

In addition, we try to understand changing exposure to flood hazard from another angle by examining the absolute number changes (Table 16), which is specific to the story portrayed by percentage change in Figure 36. For airports, although the absolute number of assets doesn't change much, the number of customers experiencing increasing or decreasing flood hazard varies significantly between regions. For other assets, the absolute number differs between regions as well as the number of customers. Thus, when we study exposure to changing climate hazard, we must not examine the aggregate numbers, but disaggregate the analysis to individual assets, the region, and the indirect exposure experienced by the people reliant on the particular infrastructure asset and network.

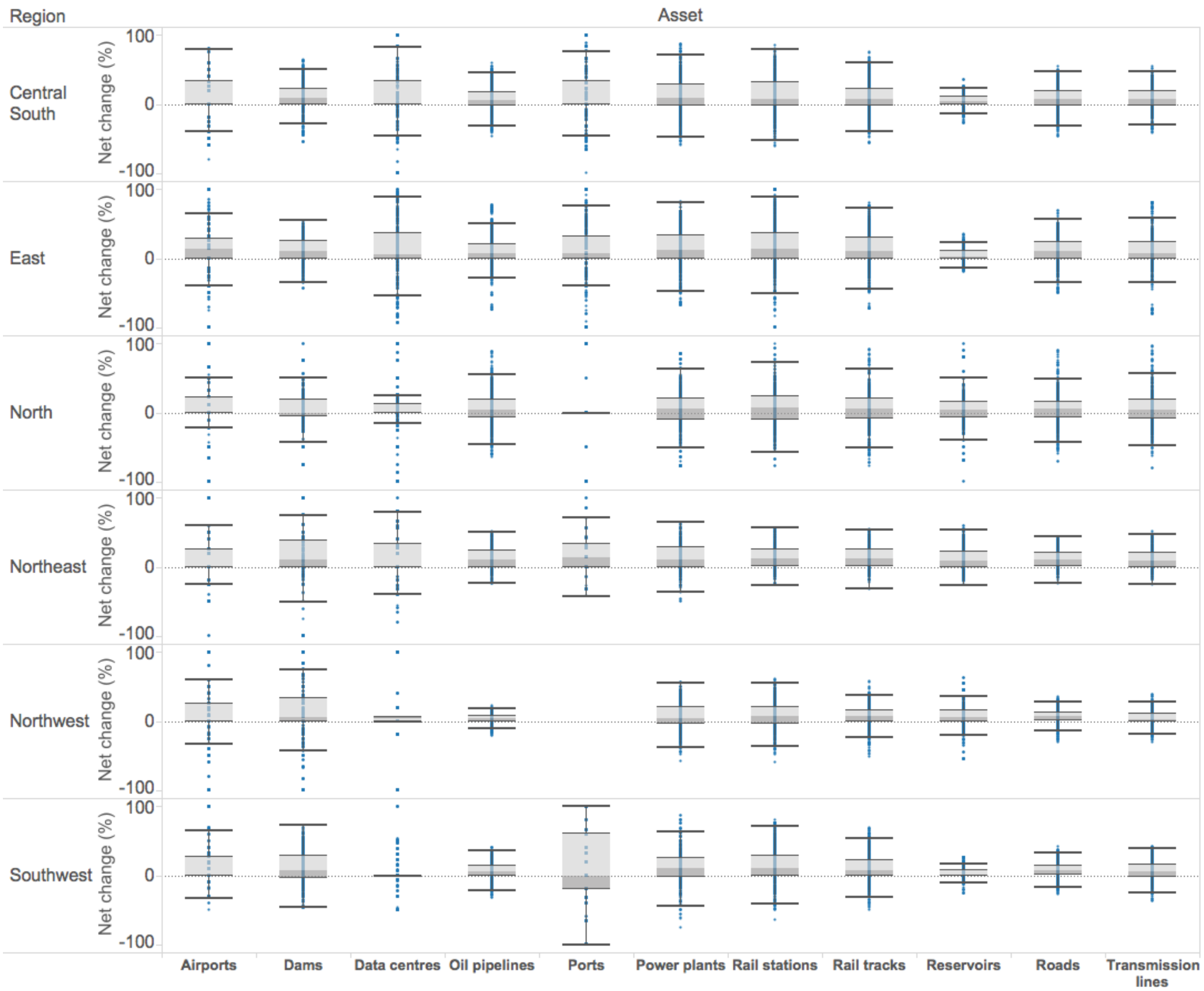


Figure 36. Net percentage change of all infrastructure assets and networks (airports, dams, data centres, oil pipelines, ports, power plants, rail stations, rail tracks, reservoirs, roads and transmission lines) exposed to changing flood probabilities. Regional variation.

Overall, our results demonstrate, for the first time, how China's infrastructure stocks are exposed to changing flooding hazards due to climate change, covering eleven types of infrastructure assets and networks. Not only are we able to examine locational exposure of infrastructure assets and networks; we demonstrate the regional variation of exposure for all assets. More importantly, we estimate the number of customers who rely on the infrastructural services and are not necessarily on the floodplain. One limitation of this study is that we have not included flood protection levels for individual infrastructure assets. Another is that we have not assessed how infrastructure stocks, infrastructure usage rates and population dynamics might change, which would be important for studying changing future exposure. However, these changes depend on socio-economic factors that are impossible to predict. Whilst scenarios like the Shared Socio-economic Pathways (SSPs) are of value in exploring a range of development trajectories at a national scale, understanding flood exposure involves pinpointing where new assets will be located, which is beyond the feasibility of scenario exercises. Even if we were to simulate changing infrastructure vulnerability, the results of these simulations would be very difficult to interpret. We are more able to interpret the effects of climatic changes on flood probability by focusing upon existing infrastructures and their customers. Whilst recognising the limitations of our study, we can draw some important policy conclusions. First, flooding poses a real threat to existing infrastructure stock as projected by most climate models; therefore adaptation is a necessity. Second, the same infrastructure stock faces a range of potential threats. The scale of projected change depends on the warming scenario (RCP 4.5 and 8.5), the climate model, the time period, and characteristics of individual assets as well as the geographical location. Thus, in order to understand the changing exposure of infrastructure assets to climate-induced flood hazards, one must take all these factors into account. Last, improving standards for future infrastructure assets should be a consideration, given many of the assets are designed for a lower return period than perhaps they ought to have been, reflecting a relatively high discount rate favouring the present over the future at the moment. Indeed, current discount rates for infrastructure projects in China are set at 8% (Chinese Ministry of Housing and Urban-Rural Development 2006), which is high compared to countries such as the UK which is set at 3.5% (UK HM Government 2013). Yet the long-term nature of infrastructure projects means that the benefits and costs of climate change have to be taken into account, implying that a lower discount rate should be adopted. For existing infrastructures, one must examine ways in which we could improve the resilience of these assets and networks so that they can cope with increasing hazards should they occur.

Table 16. Regional net change in absolute terms (range)

Asset	Net change in absolute terms	Northeast (东北)	Central South (中南)	East (华东)	North (华北)	Northwest (西北)	Southwest (西南)
Airports	**Assets**	[-2, 3]	[-4, 4]	[-5, 6]	[-4, 5]	[-4, 6]	[-5, 7]
	Customers	[-11142310, 11142310]	[-48309410, 48309410]	[-33828726, 33828726]	[-81973155, 81973155]	[-24640006, 24640006]	[-2737325, 31428882]
Dams	**Assets**	[-13,23]	[-23,35]	[-18, 38]	[-10, 10]	[-11, 10]	[-51, 75]
	Customers	n/a	n/a	n/a	n/a	n/a	n/a
Data centres	**Assets**	[-4,4]	[-20,22]	[-28, 29]	[-15, 16]	[-1, 2]	[-6, 7]
	Customers	n/a	n/a	n/a	n/a	n/a	n/a
Ports	**Assets**	[-3,7]	[-9, 9]	[-12, 13]	[-2, 2]	n/a	[-5, 5]
	Customers	[-1190000, 1527000]	[-3256200, 3256200]	[-9479533, 9479533]	[-249000, 249000]	n/a	[-2780000, 2780000]
Power plants	**Assets**	[-20, 26]	[-115, 130]	[-69, 77]	[-43, 52]	[-23, 28]	[-49, 66]
	Customers	[-22293442, 26194816]	[-41476942, 49352936]	[-25937575, 46269910]	[-32765390, 36259024]	[-8061633, 10094472]	[-21483239, 32453244]
Rail stations	**Assets**	[-56, 170]	[-31, 40]	[-40, 53]	[-69, 119]	[-44, 46]	[-76, 112]
	Customers	[-24820000, 67890000]	[-27010000, 45260000]	[-30660000, 32120000]	[-43070000, 45990000]	[-12410000, 18250000]	[-31390000, 33580000]

Reservoirs	**Assets**	[-33, 58]	[-50,59]	[-37, 69]	[-13, 18]	[-12, 18]	[-14, 19]
	Customers	n/a	n/a	n/a	n/a	n/a	n/a
Oil pipelines	**Assets**	[-777, 1476]	[-1830, 2361]	[-922, 1646]	[-1936, 2110]	[-874, 1743]	[-884, 949]
Rail tracks	**Assets**	[-1255, 3385]	[-2184, 2819]	[1508, 2744]	[-2398, 3456]	[-2217, 2468]	[-1470, 2130]
Roads	**Assets**	[-2092, 7755]	[-7237, 8416]	[-4203, 8115]	[-4815, 8945]	[-4373, 10012]	[-5313, 10558]
Transmission lines	**Assets**	[-1628, 3704]	[-2259, 3074]	[-2759, 4923]	[-1444, 2286]	[-782, 929]	[-1467, 1596]

7.3. Methods

To examine how China's infrastructure assets and networks are exposed to changing flooding risks due to climate change, we firstly apply and downscale the CaMa-Flood model for 21st century China for RCP 4.5 and RCP8.5 at return periods greater than 30, 50 and 100 respectively. Based on these results, we then compute how the probability of flooding may change for specified geographical locations in China and superimpose the infrastructure assets and network database we collected on the changing flood hazard maps. This way we are able to pinpoint the exact infrastructures that face increasing, decreasing or non-changing flooding probabilities due to climate change. Further to this analysis, we calculate the number of customers each infrastructure asset serves, according to population and data usage data. As such, we not only show those potentially vulnerable infrastructures but also the people who are dependent on them yet may not necessarily live on the floodplain. The different steps we take are described as follows.

Changing flooding risks

We drive a global river routing model – Catchment-Based Macro-scale Floodplain (CaMa-Flood) – using the daily runoff of the Atmospheric and Oceanic General Circulation Models (AOGCMs) at a spatial resolution of 1° x 1°[11]. The CaMa-Flood model routes the runoff input simulated by a land surface model into the oceans or lakes along a prescribed river network (Yamazaki et al. 2011). It calculates river channel storage, floodplain storage, river discharge, river water depth, and inundated area for each grid cell at a spatial resolution of 0.25° x 0.25°. A recently developed Global Width Database for Large Rivers (GWD-LR) is also incorporated into it (Yamazaki et al. 2014).

For the AOGCMs, we adopt a historic (1970–2005) and future period (2006–2100[12]) at representative concentration pathways (RCP) 4.5 and 8.5 (Stocker et al. 2013). RCPs 4.5

---

[11] The full list of AOGCMs is available in the supplementary materials section of Hirabayashi et al. (2013), in Table S1.

[12] For most of the AOGCMs, the period is 2006-2100. For BCC-CSM1.1, we have 2006-2099.

and 8.5 are part of a new set of scenarios used in the new climate model simulations carried out under the framework of the Coupled Model Inter-comparison Project Phase of the World Climate Research Programme. According to IPCC AR5, the RCPs are consistent with a wide range of possible changes in future anthropogenic (ie human) greenhouse gas (GHG) emissions. RCP 4.5 assumes that global annual GHG emissions (measured in CO_2-equivalents) peak around mid-century and then stabilise around 2100 whereas RCP 8.5 emissions continue to rise throughout the 21st century (Moss et al.,2010 in IPCC 2014). From the daily river-routing outputs, we extract the annual maxima value of the river water depth (spatial resolutions: 0.25° x 0.25°) for each AOGCM (1970-2100 (131 years) or 1970-2099 (130 years).

For each grid-cell within each AOGCM, we extract the annual maxima river water depth of the period 1970–1999 to quantify the Gumbel distribution parameters, which represent extreme value statistics for the late 20th century. With these parameters, we estimate the return period of the annual maxima for 1970–2100 and 1970–2099. Based on the Gumbel distribution parameters of the baseline period (Hu *et al.*, 2016, Section 3.4.1), we calculate the 'equivalent' river water depth of the baseline for each AOGCM as a way of reducing bias.

Using high resolution DEM maps, we downscale and prepare the flood inundation map (ie flood fraction 0 to 1.0) for each AOGCM (spatial resolutions: 2.5 min x 2.5 min) (Hu et al. 2015). From these outcomes, we extract the flood extent for return periods greater than 1 in 100 years, 1 in 50 years and 1 in 30 years and produce the mean flood inundation map for 2016–2035 and 2036–2055 at RCP4.5 and RCP8.5 respectively.

With the above outcomes, we evaluate the extent of changing flooding probability, calculating the difference between two selected subsequent periods. Here we subtract the inundation value for each grid (spatial resolutions: 2.5 min x 2.5 min) and estimate the total flooded area between period 1 as defined by the difference between 1986–2015 and 2016–2035, and period 2 as defined by the difference between 1986–2015 and 2036–2055, for both pathways RCP4.5 and RCP8.5. This difference indicates how specified grids in

China would face different levels of changing flood probabilities – increasing, decreasing or a continuation of the status quo.

Changing infrastructure asset and network exposure

To demonstrate how Chinese infrastructures may be exposed to the changing probability of flooding, we identify those infrastructure assets and networks that face increasing, decreasing or non-changing flooding hazard by intersecting them with inundation cells, as estimated above. We subsequently calculate the net change, as defined by the difference between assets and networks facing increasing hazard and those that face decreasing hazard. We convert the net change to percentages for better comparison between assets. Below we explain the process of estimating the flood exposure of infrastructures.

A particular infrastructure comprises a set of geospatial assets, which is denoted by the set $I = \{a_1, \ldots, a_n\}$. In the networked infrastructures assets exist as points in space or as line elements. The point assets are assigned point coordinates in a 2D space, while the line assets are assigned line geometries in space. To understand the exposure to flooding we look at the spatial intersection of particular assets with the flood grid cells. The flood grid cells are denoted by $H = \{h_1, \ldots, h_z\}$ is space. For each particular grid cell, h_i, we first estimate the change in flood fraction Δf_i between the representative time period (e.g. 2016-2035) and the baseline (1986-2005) for the particular return period and RCP scenarios.

To estimate the area of flooding we intersect the infrastructure assets with the flood cells. For the point assets, we find all assets within flood grid cells, while for the line assets we find the section of the line elements intersecting the flood grid cell. We assemble the results based on whether the change is flood fractions are positive (for increasing flood exposures) or negative (for decreasing flood exposures). Hence, two types of results sets are created:(1) $P = \{a_j : a_j \cap h_i \text{ and } \Delta f_i > 0\}$ for all assets with positives (increases) in flood exposures; (2) $N = \{a_j : a_j \cap h_i \text{ and } \Delta f_i < 0\}$. Subsequently the number of assets at increasing exposure to flood are estimated as $|P|$, and those at decreasing exposure to flooding are estimated as $|N|$, while the assets with no-changes in flood exposures are estimated as $|I| - |P| - |N|$.

For line elements, we also calculate the length of section corresponding to each type of flood exposure. The lengths of sections are estimated as: (1) $L(P) = \{l(a_j): a_j \cap h_i \text{ and } \Delta f_i > 0\}$ for increasing flood exposure; and (2) $L(N) = \{l(a_j): a_j \cap h_i \text{ and } \Delta f_i < 0\}$ for decreasing flooding. The total lengths for increasing flooding are $\sum_{L(P)} l(a_j)$, for decreasing flooding are $\sum_{L(N)} l(a_j)$, and for no-change in flooding are $\sum_I l(a_j) - \sum_{L(P)} l(a_j) - \sum_{L(N)} l(a_j)$.

Customer exposure

To analyse changing infrastructure exposure to flood hazard further, we calculate the percentage of assets exposed to increasing, decreasing and non-changing flood cells for all models that have varying assumptions in terms of the return period (30, 50 or 100), time period (2035 or 2055) and RCP (4.5 and 8.5). This is important because when floods hit, not only are the assets and people in the area affected but there may be indirect impacts. Those customers who rely on a particular infrastructure asset, for example, a power plant, may also be affected. Here we calculate the number of customers each infrastructure asset serves based on a set of user allocation models (Hu et al. 2015).

For power plants, we allocate users to each plant based on data on actual output per plant and electricity consumption per capita for the particular province in which the plant is located. The number of users per power plant, C_p, is given by the equation:

$$C_p = P_a * \frac{E_{p,a}}{D_a}$$

where $E_{p,a}$ is the energy output in megawatt-hours per year for power plant p in a particular province a; $\mathrm{D_a}$ is the electricity consumption (in megawatts per hour) of province a; and $\mathrm{P_a}$ is the population of province a.

For rail tracks, we construct an origin-destination map of the Chinese railway network based on a national train timetable and verify the dataset with the OpenStreet dataset. We assign passenger numbers over track paths by recording the stations each train journey passes through. We obtain data on the number of passengers each train carries and aggregate the total flow of passengers on a yearly basis. For rail stations, we approximate the number of users through each station by the way it is defined (Table 19 in Supplementary Information). The Ministry of Rail (now the China Railway Corporation) classifies all railway stations into six categories, depending on the type of use (passenger, cargo, marshalling yard or a mixture), sizes of passenger flow, cargo volumes and "strategic importance"(Ministry of Rail 1980). Each station is assigned a daily passenger number using the minimum threshold and aggregate passenger number on a yearly basis. For airports and ports, we collect the annual passenger statistics based on 2012 data.

7.4. Supplementary Information

Supplementary Tables

Table 17. Infrastructure asset datasets (Hu et al. 2014; Hu et al. 2015; Ministry of Housing and Urban-Rural Development 2014)

Sector	Sub-sector	Asset type	Number of assets	Completeness (%)	Flood protection range (in return period)
Energy	Electricity	Power plants	3755	100	[50, 100]
		Transmission lines (220 kv AC)	847	14[13]	[30, 100]
	Natural gas, liquid and solid Fuels	Pipelines (crude oil, natural gas, produced oil)	157	92	[20, 100]
Transport	Roads	Roads	3752	17.9	[0, 100]
	Rail	Rail tracks	42739	100	[50, 100]
		Stations	5430		n/a
	Shipping	Ports	237	4.5	[5, 100]
	Aviation	Airports	147	80	[20, 100]
Water	Water supply	Reservoirs	2532	100	[10, 300]
		Dams	935	0.8[14]	Unknown
Digital communication	Mass data and computation facilities	Data centres	385	Unknown	[50, 100]

[13] Data for 2015

[14] Total number of dams comes from InternationalRivers.org (https://www.internationalrivers.org/programs/china)

Table 18. Regional categorisation of provinces

Region	Region (Chinese)	Provinces
North	华北	Beijing, Tianjin, Hebei, Shanxi, Neimenggu (Inner Mongolia)
Northeast	东北	Liaoning, Jilin, Heilongjiang
East	华东	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Central south	中南	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan
Southwest	西南	Chongqing, Sichuan, Guizhou, Yunnan, Tibet
Northwest	西北	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
Hongkong, Macau, Taiwan	港澳台	Hongkong, Macau, Taiwan

Source: adapted from Ministry of Civil Affairs 2017 (http://mz.dmw.gov.cn)

Table 19. Railway stations classification and their associated daily passenger and cargo volumes

Railway station classification	Railway use (passenger, cargo, yard)	Average daily passenger flow	Average daily cargo volume (trucks)
Special	Single use	> 60000	> 750
	Multi-use	> 20000	> 450
1	Single use	> 15000	> 350
	Multi-use	> 8000	> 200
2	Single use	> 5000	> 200
	Multi-use	> 4000	> 100
3	Single use	n/a	n/a
	Multi-use	> 2000	> 50

Source: Ministry of Rail 1980

Supplementary Figures

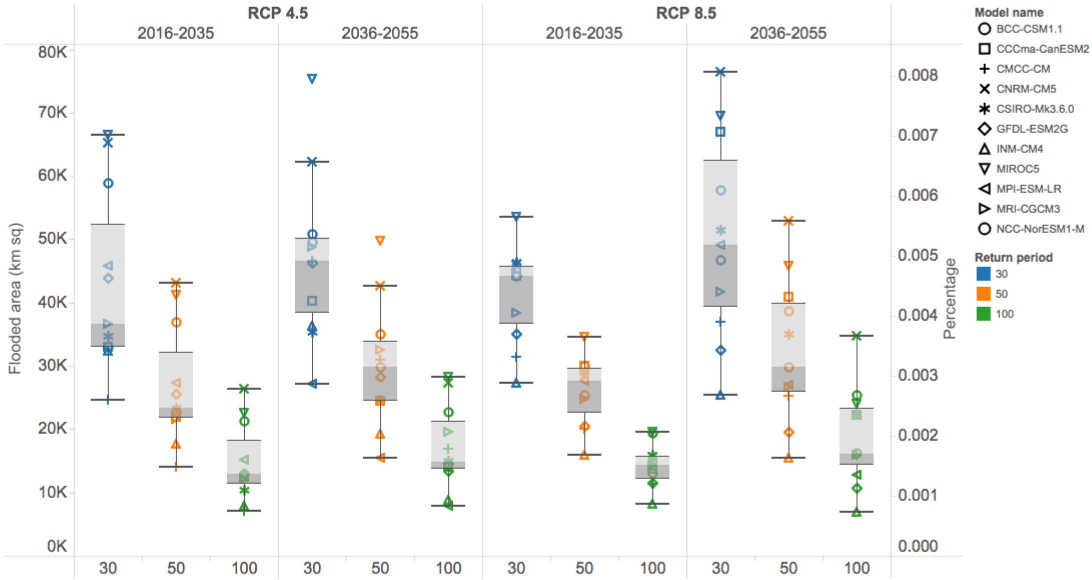


Figure 37. Projected flood area (km2) in China for all AOCGMs given different return periods (> 1 in 100 years, > 1 in 50 years, >1 in 30 years) and radiative forcing assumptions (RCP 4.5 and RCP 8.5).

Colour (blue, orange and green) shows details of return period. Blue indicates return period of 30 or greater; orange indicates return period 50 or greater; green indicates return period 100 or greater. Shape shows details of AOGCM model name. There are two future time periods: period 1 (2016–2035) and period 2 (2036–2055). Overall, there are 132 model variations depending on the return period, the time period, RCP and AOGCM model assumptions.

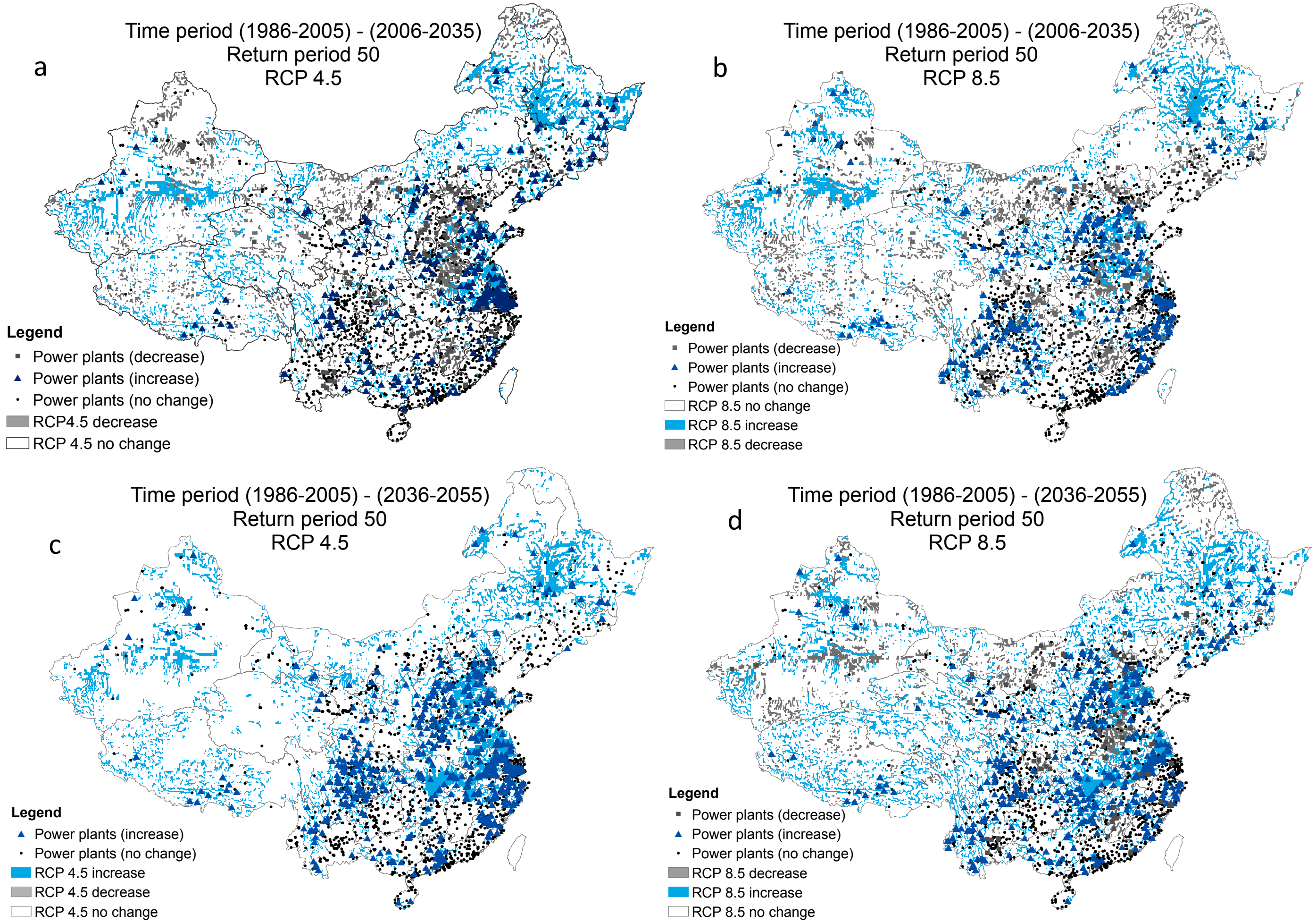


Figure 38. Locations of power plants exposed to changing (increasing, decreasing, non-changing) flood hazard for model MIROC5. Squares are power plants facing decreasing flood hazard; triangles are power plants facing increasing flood hazards; circles are power plants facing non-changing flood hazards. All figures are for return periods greater than 50, but we vary RCP (4.5 in Figures 38a and 38c; 8.5 in Figures 38b and 38d). Time period (1986–2005) to (2006–2035) is shown in Figures 38a and 38b whereas time period (1986–2005) to (2036–2055) is shown in Figures 38c and 38d.

8. China’s Infrastructure (R)evolution: Exploring the Drivers of Infrastructure Development

8.1. Introduction

Between 1992 and 2013, China annually invested 8.5% of its GDP into its infrastructure, due to which its stock of infrastructure as a percentage of GDP is at 71%, above the global average (Dobbs et al. 2013). However, the relationship between this investment and China’s economic geography is complex. As in all countries, infrastructure development in China reflects the dynamic interplay between multiple endogenous and exogenous processes. Endogenous processes include population growth, migration, economic growth, industrialization and urbanization. Exogenous processes, on the other hand, include government planning, shocks such as environmental disasters, and access to foreign donors. The interplay between these processes will determine future infrastructure development. Not only will this have far-reaching impacts on China’s own development; given the country’s rise as an economic and political power, it is also increasingly significant for the rest of the world.

Using a previously unavailable dataset with approximately 9,000 nodes and 8,000 lines across five different infrastructure sectors – energy, water, transport, waste and ICT – between 1900 and 2010, this paper analyses the evolution of China’s infrastructure development processes across space and time. While current literature often takes an economic, political or social perspective exclusively, and focuses on one sector only, we bring all these perspectives together.

Section 8.2 explores theoretical and empirical lessons related to infrastructure development in other countries. Section 8.3 describes the development of China’s infrastructure system, substantiating that narrative with new empirical data. Section 8.4 presents our framework of infrastructure development drivers in China, based on the observed historical development trajectory, extensive policy documents and interviews.

Building on our framework of infrastructure development, we consider prospects for the future in Section 8.5 and conclude in Section 8.6.

8.2. Lessons from theory and other countries

Heinsz (2002) argues that there are three groups of determinants affecting infrastructure investment: growth theory, political institutions and investment, and economic characteristics. Building on his analysis, we look at infrastructure development more broadly, classifying two strands of theoretical discussions of the subject: economic perspectives, and political institutions and investment.

8.2.1. Economic perspectives

From a macro-economic perspective, infrastructure is often lumped with other forms of capital. A dominant strand of this literature is concerned with neoclassical growth models (e.g. Solow and Koopman), which explain long run economic growth by looking at capital accumulation, labor or population growth, and technological progress. A key assumption in the short run is that capital is subject to the effects of increasing and diminishing returns in a closed economy. Early in the development process, network effects specialization and economics of scale mean that the marginal benefits of infrastructure provision increase. Conversely, as the economy converges, returns on infrastructure investment diminish because of high cost of infrastructure provision in dense urban settings and because later infrastructure investments are often aimed at dealing with congestion at peak times so utilization may not be high. These increasing and diminishing returns are often depicted as an S-shaped logistic curve whereby we see relatively low to moderate growth rates in the initial decades after the initial penetration of infrastructure services, followed by a rapid acceleration of growth and then a deceleration in mature economies.

Many economists have demonstrated an empirical association between growth and infrastructure (Canning 1997; Munnell 1992; Czernich & Falck 2009; Hou & Li 2011). Seminal work by Aschauer employed cross-sectional state-level data on gross state product and public infrastructure expenditure 1965 and 1983 and provided evidence that infrastructure investment was key to the economic "golden age" of the 1950s and 1960s (Aschauer 1990). Assessing 64 empirical papers, Straub found a positive and significant link between infrastructure and some development outcome (Straub 2008). However, while most agree that there is a correlation between economic growth and infrastructure development, the evidence for the direction of causality is unclear. Some scholars have found contradictory results if different measures of growth are applied. For example, Banerjee and others show that proximity to transportation networks has a moderately positive causal effect on per capita GDP levels across sectors, but no effect on per capita GDP growth (Banerjee et al. 2012). Results may also differ depending on the time effect: one would not expect the growth in the capital stock in one year to be correlated with the growth in output in the same year (Nadiri & Mamuneas 1994).

A range of economic models – namely New Economic Geography (NEG), Land Use Transport Interaction (LUTI) and Spatial Computable Generable Equilibrium (Spatial CGE) – have sought to explain the influence of infrastructure development on the spatial distribution of economic activities. NEG models predict empirically observed patterns of the core-periphery spatial structures and income disparities within a country, incorporating three endogenous processes – increasing returns to scale, transport costs and the movement of factors of production (Fujita 2010; Redding 2010). Land Use Transport Interaction models are often used to assess the economic impacts of transport investment on the property and labor markets. Infrastructure is modelled in terms of its effect on generalized costs of travel to work, or indirectly in the general attractiveness function for different locations. Spatial CGE models are spatial extensions of Computable General Equilibrium (CGE) models (Oosterhaven et al, 2001), which simulate entire economies through functions that describe the behavior of economic agents operating in markets at equilibrium, and include infrastructure as transport networks that are incorporated as costs (Robson and Dixit 2005).

Thus, economic theory and empirical evidence provide some insights and frameworks for interpreting infrastructure development in China – notably the macro- and geographical economic effects of infrastructure investment. However, even a cursory inspection of China’s infrastructure development reveals how it has been shaped by government intervention, both directly through state investments and indirectly through policies of regional economic development and migration.

8.2.2. Political and institutional perspectives

Given the inevitable involvement of governments, to a greater or lesser extent, patterns of infrastructure development may be explained better by political economy than by economic efficiency (Canning 1997). Political motives may include the provision of employment, the desire to improve services to key constituencies, concern over the limitations of private provision, a desire to urbanize and industrialize (Jacobson & Tarr 1995; Swyngedouw et al. 2002), and colonization (for example, China and India’s infrastructure development during their colonial era). Economic conditions play an important political role in the pattern of infrastructure investment (Heinsz 2002). For instance, the Tennessee Valley Authority (TVA), part of the New Deal charted by the US Congress in 1933, was motivated by political upheaval in response to the Great Depression (Culvahouse 2007). Environmental legislation has mandated standards for waste water treatment, disposal of solid waste and emissions from power plants and transport systems, leading to major investments in new and retrofitted infrastructure (Jacobson & Tarr 1995).

The state’s role in ownership of infrastructure differs geographically through time and depending on the sector. The transition of infrastructure from fragmented pre-industrial arrangements to public hands happened at different times for different sectors and countries. For instance, reformers in late-nineteenth century England concluded that sanitation was too important an urban function to be left in the hands of profit-motivated contractors (Hering and Greeley in Jacobson & Tarr 1995). England accordingly developed a public urban network of sewers and waste treatment plants. In the Netherlands, wide economic-cultural-political transformations led the public authorities, who initially preferred leaving waste treatment to the private sector, to invest in piped water infrastructure (Geels 2005). Late industrial eras meanwhile have been characterized by a shift back to private ownership, driven by public debt (i.e. the desire to raise revenue by selling public assets and shift new investments off the public balance sheet) and/or focus on privatization as a means to increase efficiency at a time of otherwise decreasing returns to infrastructure investment.

Versions of these factors also exist in China, though in a distinctive political and cultural context which we will discuss in Section 8.3.

8.3. Evolution of infrastructure development in China

In 1949, when the People's Republic of China was founded (Figure 39), the country inherited a limited amount of infrastructure stock after decades of civil strife and war (Figure 40). Between 1949 and 1957, there was a national strategy of intensive industrialization whereby the number of statutory cities grew from 120 in 1949 to 176 by the end of 1957, and the urban population grew rapidly from 10.1% of the national population in 1949 to 15.4% in 1957 (Li and Yu 2008, in OECD 2009). To foster this growth, infrastructure was built in these cities and expanded fast.

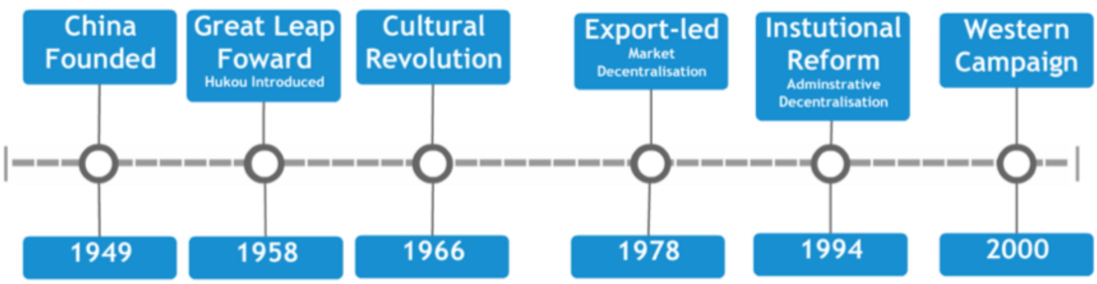


Figure 39. A political and economic timeline of China's development since 1949.

Source: authors' own data and interpretation.

However, this investment slowed after 1957. The "Great Leap Forward" (1958-1960)

– an ambitious attempt to rapidly industrialize – and led to a colossal expansion of the urban population, by 31 million, due to the influx of a rural labor force (OECD 2009; Lardy & Fairbank 1987). Figure 40 demonstrates initial waves of increases in both water and transport sectors, followed by decreases towards the end of 1960. Cities did not have the infrastructure in place to cope with this expansion. In an attempt to cope with this deficiency, the Chinese government introduced the "Hukou" System that restricted movement between urban and rural residents, which mitigated to some extent the pressure from migration into cities on overused infrastructure services (McKinsey 2009). We observe that passenger freight indeed rose and slowed moving towards 1960.

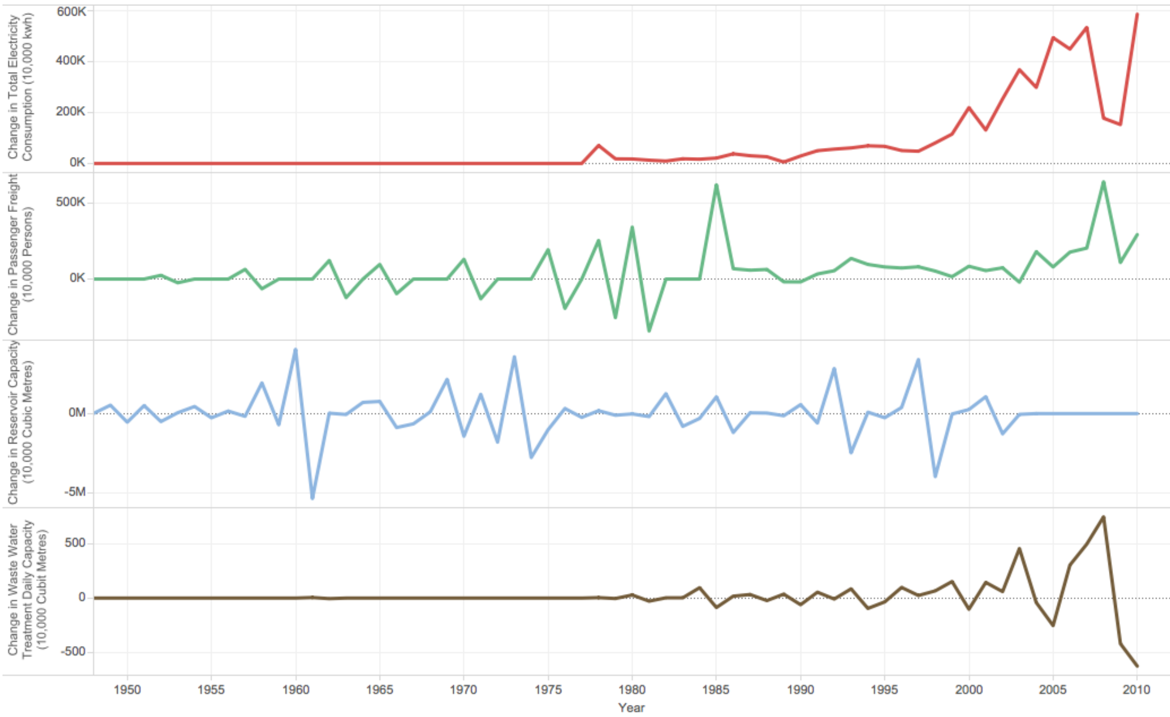


Figure 40. Evolution of China's infrastructure system in selected sectors – electricity, reservoir, wastewater, transport.

Source: authors' own data and analysis.

Not surprisingly then, between 1960 and 1980, China's infrastructure grew relatively slowly owing to the turbulent environment and a general lack of funding (Figure 40). There were some exceptions, however: during this period, there was substantial investment in the water and aviation sectors, although subject to much volatility. The construction of water infrastructure was popular because reservoirs simultaneously provided irrigation for rural agriculture, flood control and a water supply. Reservoir storage capacity was at 117.4 billion cubic meters in 1961; by 1979 it had increased to 275.6 billion cubic meters. The investment in water and aviation is also evident in Figure 41, which shows the spatial evolution of selected infrastructure sectors: airports, power plants, wastewater treatment plants and reservoirs. For military reasons, airports were built and relatively evenly spread across the country. Other assets such as power plants and reservoirs reflect resource constraints in that power plants were concentrated along the resource basins (the central coal belt) and reservoirs on rivers.

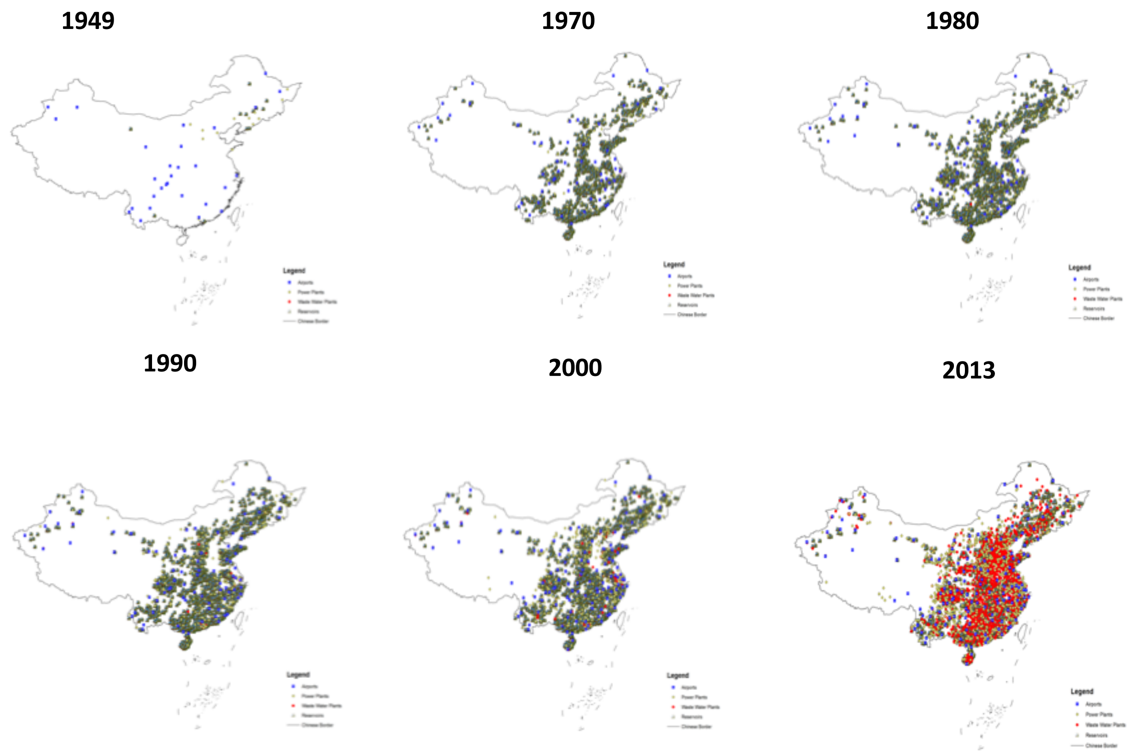


Figure 41. Spatial evolution of selected infrastructure sectors: airports, power plants, wastewater treatment plants and reservoirs.

Source: authors' own data and analysis.

When China adopted an export-led economic development strategy in the 1980s, early infrastructure investment was mostly to facilitate the establishment of special economic zones and open coastal cities (Liu 2006). One can observe in Figure 41 a clustering of infrastructure assets along the coast after the 1980s. In these areas, infrastructure investment was concentrated heavily on port capacity and road transport links in a few selected harbor cities. However, such investment in the transport sector at the national level remained low; for example, between 1981 and 1990, China's investment in ports, roads and railways amounted to only 1.3% of the GNP (Rimmer 1997). In fact, freight passenger numbers plummeted at the beginning of the 1980s and peaked around mid-1980s. A key element of this limited investment was to provide for the north-south movements of people and freight to complement the ready-made, east-west arteries supplied by the Yangzi and Yellow rivers, and for coal movement from north to south and southeast (Rimmer 1997; National Development and Reform Commission 1987).

During the same period, investment in the water sector and electricity steadily continued, to fuel the rapidly growing economy (Figure 40). Reservoir storage capacity increased from 278 billion cubic meters in 1980 to 323 billion cubic meters in 1990 and many new reservoirs were built along the Yangtze River, as shown in Figure 41. These reservoirs were built for a variety of reasons including irrigation, hydropower, flooding detention, aquaculture, tourism, shipping transport improvement and water supply. Electricity output rose almost two-fold. Planned investment in fuel production between 1981 and 1985 reached 58.3 billion RMB compared to the 29.8 billion RMB[15] invested in the transport system (National Development and Reform Commission 1982). In addition, towards the end of the 1980s, digital infrastructure was emphasized as a priority area (National Development and Reform Commission 1987).

After the 1990s, infrastructure could again no longer sufficiently support the rapid growth in industrial production (National Development and Reform Commission 1990). For instance, urban water infrastructure for more than 300 cities in China (among a total of 658) could not provide sufficient supplies, leading to daily shortages of about 6.6 m^3 on

[15] 29.8 billion RMB is the equivalent of 19.86 billion US Dollars. Calculated based on an exchange rate of 1.5 (KPMG 2012).

average[16] (Wu 1999). Insufficient urban road space led to severe traffic congestion and the average travel speed inside cities was less than 12 km per hour. Less than 7% of urban wastewater was treated (*Ibid*).

In response to this lack of infrastructure capacity, a decision was taken to massively increase investment. Annual capital expenditures for transport, electricity, piped gas, telecommunications, urban water supply and sanitation rose steadily from US$39 billion in 1994 to US$88 billion in 1998 (Liu 2006). The Chinese reaction to the East Asian financial crisis in 1997 was to increase spending on infrastructure to minimize the impacts of the crisis (*Ibid*). Figure 40 shows that capacity increased for most sectors post 1997, except transport which experienced a slight decrease. Electricity consumption increased three-fold from 3.14 billion kwh in 1990 to 11.3 billion kwh in 2000, and the average growth was a remarkable 13% per year. Total passenger volume was at 7 billion person-trips at the beginning of the 1990s; by 2000, it had reached more than 32 billion. Reservoir capacity, at 323 billion cubic meters in 1990, had increased to 407 billion cubic meters by 2000. In addition, an institutional reform in 1994 transferred more fiscal autonomy from the central government to local governments, which meant that infrastructure projects below $300 million could be approved and financed locally (*Ibid).* Owing to this 1994 reform and a sustained period of growth with a larger capital base, infrastructure investment became rife (Wu 1999). From the mid-1990s growth accelerated in all sectors. In particular, the urban waste sector developed very fast – daily treatment capacity increased from 3.9 million cubic meters in 1990 to 18.1 million cubic meters in 2000.

Infrastructure was attractive as an investment because it provided a quick stimulus to employment and GDP, alongside handsome returns for the construction and real estate sectors. As a result, many cities 'overinvested'. In response to this soaring growth, the ninth Five-Year Plan specifically dictated that infrastructure planning should focus on strategically building additional "backbone" projects, rather than "blindly constructing duplicating projects" (National Development and Reform Commission 1996).

[16] 16 million tons in the original document. Converted to m^3 at rate of 0.42.

Towards the latter half of the 1990s, as urban infrastructure investment was devolved more to local governments, the national planning of infrastructure became increasingly trans-regional in nature. This was also to facilitate a longer-term planned development path (to 2010) that more clearly defined the economic roles of different regions in China. According to this plan, the east/southeast coast was to concentrate on higher-value-added industries whereas the north/middle regions were to focus on agricultural/energy/raw materials and manufacturing production; the western region was to build more infrastructure to elevate growth in the region and facilitate development in the rest of China (*Ibid*). With different regional roles, infrastructure projects needed to be well connected and coordinated; therefore, mega projects largely funded by the central government at trans-regional scales were undertaken. For instance, four "trunk roads" were constructed across the country (more details in Section 8.3.2), and Qinhuangdao, Tianjin, and Huanghua ports were created to facilitate the transportation of coal to eastern and southern coal bases (*Ibid*).

The 2000s marked yet another wave of remarkable growth (Figure 40). The pace at which electricity consumption grew was a steady 13.3% per annum; total consumption increased from 12.6 billion kwh in 2001 to 45.9 billion kwh in 2010. Passenger volume grew from 14.7 billion in 2000 to 32.6 billion in 2010 – a steady increase of 8% per year. In the same period, reservoir capacity grew from 410 billion cubic meters to 424 billion cubic meters. Waste water treatment growth rocketed owing to the introduction of the 2006 "energy conservation and emissions reduction" policy which encouraged investment in minimizing waste. The daily treatment rate increased from 18 million cubic meters in 2000 to 125 million cubic meters in 2010. Figure 41 demonstrates this striking growth; wastewater treatment plants (the red dots) sprang up in this decade.

By the 2010s, as Figure 41 shows, infrastructure was unevenly spread, with much of it concentrated along the coast, middle and northeast of China. This correlates with the regional imbalance brought about by an export-led development model after the 1980s. In response to this, the "Western Campaign"[17] was proposed to utilize natural resources in the west for further development and balance the regional disparities that had previously favoured coastal regions (National Development and Reform Commission 2001b). It is important to note that this was not a development strategy exclusively focused on western China; rather, it aimed to maximize the comparative advantages of different economic regions so that growth in the west could also benefit the development of advanced eastern areas.

In addition to balancing development progress in the West, the "rural economy", which emerged as a development strategy in the Eleventh Five-Year Plan (2006-2010), required substantial investment in infrastructure. For instance, the Plan stated that the country was to construct and upgrade 1.2 million km of rural roads, and establish 50 green energy (wind/hydro and solar power) demonstration counties to provide electricity for the first time to 3.5 million rural villagers (National Development and Reform Commission 2005).

The 2000s also marked the onset of a slow transition from a low-end manufacturing-based economy to a service-based economy. To facilitate this transition,

[17] There were four mega infrastructure projects involved in this "Campaign". First, the "West-to-East Project" delivered electricity from the western regions to the east. Between 2001 and 2010, the total investment in the "West-to-East Project", excluding the Three Gorges Dam, amounted to over 1 trillion RMB (China Southern Power Grid 2011). High-voltage transmission grids were built to serve three transfer routes – "North, Central and South" – that took electricity generated in western China to the eastern regions where power shortages had been problematic (National Development and Reform Commission 2001a). Second, the "South-to-North Water Diversion" project transferred water from the upper, middle and lower reaches of the Yangtze River (South-to-North Water Diversion Committee 2006). With an investment of around 500 billion RMB, the planned three routes of the South-to-North Water Diversion: "East, Middle, West" pipelines would divert a total of 44.8 billion cubic meters of water (*Ibid*). Third, the "West-to-East" project was built to transfer gas from the Tarim gas field in Xinjiang province in the west to the east of the Yangtze River Delta region (China State Council 2006). Pipelines with a total length of 4000 km pass through 10 provinces (*Ibid*). Fourth, the "Qinghai-Tibet Railway" is a 1,142 km long railway line that runs from Qinghai to Tibet. As of 2006, the project had seen a total investment of 21.4 billion RMB (Chinese Government Network 2006).

the tenth Five-Year Plan (2001-2010) emphasized the development of information technology while keeping the legacy of heavy investments in energy and transport (National Development and Reform Commission 2001a). Indeed, infrastructure planning and construction was no longer about "quantity" but also "quality". Emphasis was placed on the upgrading of technical efficiency for new infrastructure assets – for example, one objective was to "master the engineering of ± 500 kV DC and 750 kV AC transmission grids and develop the capability for 1000 kV UHV AC and ± 800 kV DC constructing transmission equipment" (National Development and Reform Commission 2005).

Post the 2010s, the emphasis on "quality" continues in infrastructure planning. One of the many technological programs is to develop large Liquefied Natural Gas (LNG) and Liquefied Petroleum Gas (LPG) carriers (National Development and Reform Commission 2011). Infrastructure planning is also affected by China's increasingly systematic planning. An overall strategy for regional development was refined in the twelfth Five-Year Plan (2011-2015), which dictated that the west be prioritized for development; the north-east concentrate on high value-added industries such as tourism and finance; the middle should furnish hubs for agricultural products, energy and transport; and the east should focus on technological innovation (*Ibid*). In addition, the country is divided into "functional areas" – urban, agricultural and ecological. All of the above has tremendous implications for infrastructure growth in that we will observe a continued wave of infrastructure assets of all kinds being built in the west, while ICT will be the focus in the east and northeast, and transport and energy in the middle. Further, infrastructure growth will be hindered in areas defined as "agricultural" and "ecological".

8.4. Understanding drivers and trends: a framework of infrastructure development in China

After examining infrastructure development in China, we formulate a framework for it which proposes that China developed its infrastructure through a series of processes during which multiple factors – economic, social objectives and political – at different levels of government interplay. Between sections 8.4.1. and 8.4.5., we discuss some of the main processes and their relationship with infrastructure development in China.

8.4.1. Population growth

The level of demand for infrastructure services is in part determined by household demand, which is affected by the aggregate number of people in an economy and its growth rate. Indeed, many scholars include population as a key parameter in forecasting changes in infrastructure demand (Fay & Yepes 2003; Isaac & van Vuuren 2009). Whilst population increase will have a direct effect on demand, the scale of that effect depends upon other factors. For instance, income has a positive effect on per capita demand, while price increases tend to slow it down (OECD 2008).

The population in China increased from 667.1 million in 1960 to 1.36 billion in 2014 (World Bank 2015c). This relatively high growth rate was a result of the state actively encouraging population growth in the aftermath of decades of civil strife. Population growth declined steadily[18] after the 1970s as a result of the family planning programme in the 1970s and the One Child Policy introduced in 1980 (Moore 2014; World Bank 2015d). The population growth rate actually increased somewhat in the 1980s but since then has steadily decreased, with the population increasing by only 100 million since 2000.

8.4.2. Migration

The regional distribution of population is determined by the geography of fertility, mortality and migration. Since the 1990s, an extraordinary phenomenon has occurred in China, induced by the relaxation of the regulations of the Hukou (Gong et al. 2008). The last three decades have witnessed the world's 'Great Migration': an estimated 200-250 million rural residents have moved to Chinese cities and towns (Chan 2012). This process

[18] The population growth rate declined steadily except in the 1980s, when it increased.

has been instrumental in shaping the spatial distribution of households and the demand for infrastructure services, particularly in cities.

Broadly speaking, there are two types of migration in China: interprovincial and intraprovincial, the former occurring between provinces and the latter within provinces. Figure 42 shows interprovincial migration patterns in China: the most popular destinations have been in areas around Beijing, Shanghai and Guangzhou. Among the 15 highest migration recipient cities in 2007, Dongguan in Guangdong Province has the most densely populated migrant area (2,614 migrants per 0.25 sq. km), followed by Shenzhen (2,295), Wuxi (1,691) and Guangzhou (1,171) (*Ibid*). Intraprovincial migration occurs when laborers move to major cities, usually the provincial capitals. Indeed, infrastructure supply is higher in these regions, as is evident from what we observed in section 8.3.

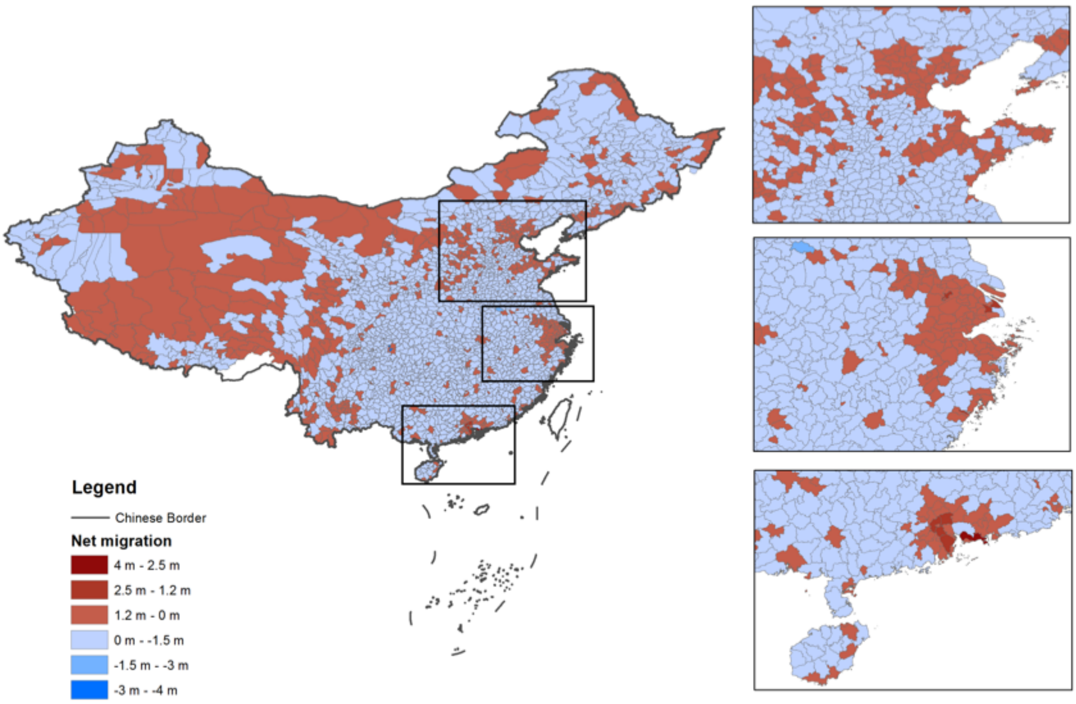


Figure 42. Migration patterns in China based on 2010 census data.

Red areas are recipient regions. White areas indicate lack of data.

8.4.3. Urbanization

China is now the world's largest urban nation, with over 600 million citizens living in cities (OECD 2009). The number of cities increased from 191 in 1978 to 667 in 1999, while the urban share of the national population increased from 18 to 31 per cent (Song & Zhang 2002). The 12th Five-Year Plan set out an urbanization rate of 51.5% by 2015, which means approximately 700 million urban residents (National Development and Reform Commission 2011). As China urbanizes, its demand for infrastructure services such as water supplies and wastewater treatment will increase. The density effect of urbanization also allows easier and cheaper access to infrastructure such as electricity and telephone services, and economies of scale in wastewater treatment (Fay & Yepes 2003). As a result, urban areas tend to have a concentration of infrastructure assets. It is clear that infrastructure assets in Figure 41 coincide with urban areas in Figure 43.

1992 **2002** **2012**

Figure 43. Urbanisation extent using DMSP-OLS night time light data from 1992 to 2012.

Perhaps the most interesting effect of urbanization on infrastructure services is geographical, in that urban areas tend to "favor" infrastructure such as electricity and telephones, whereas rural areas tend to "favor" water infrastructure. On the other hand, higher rates of urbanization are associated with more manufacturing and less agricultural production, which may explain why in the case of China, water infrastructure for irrigation and flood control, was developed first. At the beginning of the reform period, the agricultural sector occupied more than 70 per cent of the total labor force and accounted for 28.2 per cent of gross domestic product (GDP) (NBS 2007). In stark contrast, in 2006 secondary and tertiary industries engaged more than half of the total labor and contributed nearly 95 per cent of GDP (*Ibid*).

8.4.4. Economic growth and industrialization

The most fundamental driver of infrastructure development is economic growth. GDP per capita in China, a mere $89 in 1960, increased to $7594 in 2014 (World Bank 2015b). From 1979 until 2010, China's average annual GDP growth was 9.91%, reaching an historic high of 15.2% in 1984 and a record low of 3.8% in 1990 (World Bank 2015a). Many scholars have documented empirical evidence that infrastructure has been pivotal to China’s economic growth over the last few decades (Yu et al. 2012; Démurger 2001; Shiu and Lam 2004, in Sahoo et al. 2010; Banerjee et al. 2012).

Along with economic growth comes a process of industrialization, which has significant implications for the requirement of infrastructure services. During the first stage of industrialization, modelled on the former Soviet Union, China’s national industrialization policy focused on the development of heavy industry (OECD 2009) and water infrastructure.

As China entered the second stage of capital-intensive industrialization, its energy infrastructure investment increased exponentially as industry was beginning to account for a larger share of the economic structure, as we saw in Section 8.3.2. Spatially, China was broadly divided into two regions: the west provided energy and the east consumed energy, as shown in Figure 44. To fuel further industrialization, the Chinese government has planned five energy bases (Xinjiang, Ordos, Shanxi, Southwest and Mengdong bases), and constructed numerous pipelines that transfer the much-needed energy to the eastern consuming regions.

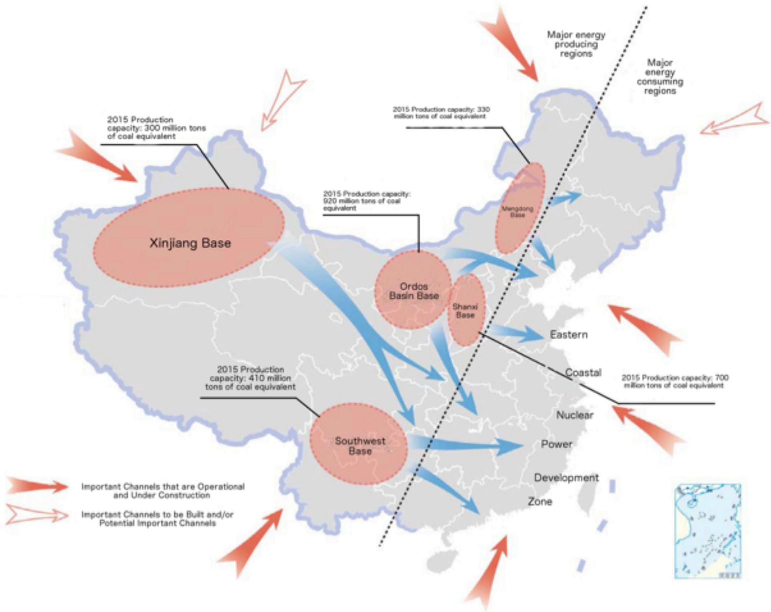


Figure 44. China's planned energy bases.

Source: China's 12th Five-Year Plan for the energy sector National Energy Administration (2011).

Transportation infrastructure such as shipping developed along the coast during the second stage of industrialization to facilitate this export-oriented economic development path and allow domestic trade. According to PONCET, the average trade openness rate (computed as imports plus exports divided by GDP) of Chinese provinces more than doubled between 1987 and 1997, increasing from 14% to 37% (PONCET 2003). On average, interprovincial trade accounted, for 88%, 80%, and 66% of Chinese provinces' total trade in 1987, 1992, and 1997 respectively, (*Ibid*). Figure 45 shows how most provinces in China, namely Hubei, Yunnan, Zhejiang, Liaoning and Hunan, are actually trading within themselves and with each other; only one province – Guangdong – stands out as having significant trade with international markets.

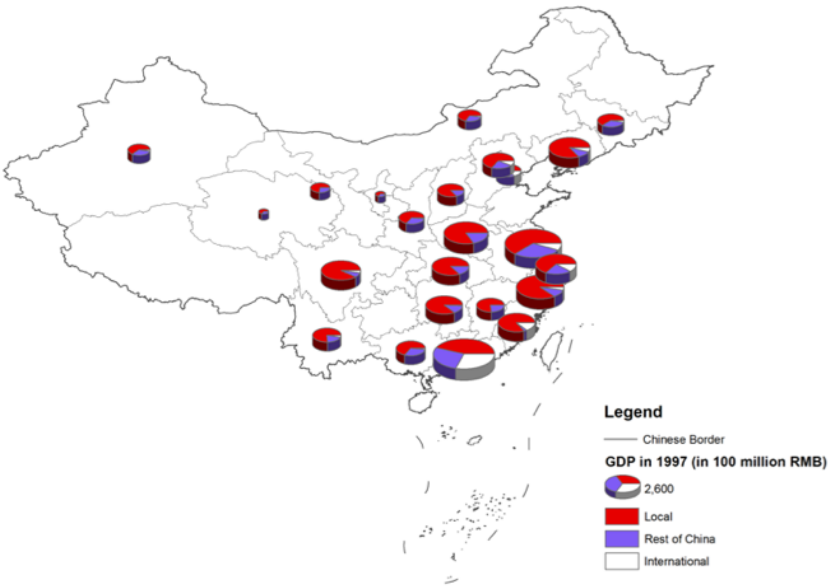


Figure 45. Provinces trading with local, rest of China and international partners.

Source: data from Provincial Input Output Tables 1997 (PONCET 2003). Data on GDP in 1997 are downloaded from www.stats.gov.cn.

During the third stage of industrialization, the transport network was developed even further, which had a significant impact on regional economic growth and trade. This third period also features a transition from low- to medium-value production. Between 1990 and 2000, the textile exports of the coastal region decreased from 32% to 26% (compared to their total exports), and those of electric and electronic materials increased from 11% to 33%, although the latter mainly involved assembly activities (Catin et al. 2005). The type of infrastructure to serve this transition has had to change, and new forms, such as digital communications technologies, have developed rapidly.

8.4.5. Government planning

Whilst many of the patterns of infrastructure investment development can be explained by trends in demographic changes and urban and industrial development, the role of planning continues to be a crucial exogenous influence that is superimposed upon these factors. In many cases, the factors – i.e. economic growth, population, rate of urbanization and industrialization – have been dictated by national plans and many of their targets have been met, as shown in Table 20. The average near-completion rate and complete completion rate stand at 70% and 58.8% respectively.

Table 20. Assessment of China's 10 Five-Year Plan target completion rate

Five year plans	Number of targets	Complete Completion rate (%)	Near-completion rate (%)	Expected time completion accuracy (%)
1st	32	84	87.5	56.3
2nd	21	0	0.0	0
3rd	39	53.8	69.2	59.0
4th	52	34.6	53.8	48.1
5th	16	31.3	75.0	75.0
6th	33	84.8	93.9	42.4
7th	28	71.4	71.4	32.1
8th	27	88.9	88.9	22.2
9th	16	75.0	93.8	68.8
10th	56	64.3	73.2	50.0

Source: Wang & Yan (2009)

Below we demonstrate the central role of planning in the energy, transport, water, waste and digital communication sectors. In particular, we examine national plans between 1981 and 2015 by conducting text analysis and identifying sections and targets of interest related to the sectors within each five-year plan. A table is synthesized outlining the major issues for that sector and a numerical target is noted where relevant. In addition, we conducted interviews with relevant sector planners to complement the text analysis and demonstrate the spatial evolution of each sector by collecting both time series and spatial data.

Energy

Energy plays an important role in China's economy, as it does in any other. It employs at least 10 million people and accounts for some 15% of sales revenue from all industrial enterprises (Andrews-Speed et al. 2010). Table 21 summarizes the relevant targets for the energy sector that are scattered across the whole text of each five-year plan. We observe how decision makers have identified and changed their priorities. All quantitative targets in energy are related to "capacity" building, although the actual targets have varied from production capacity to growth in capacity. Although coal was traditionally the dominant fuel, from the beginning of the 2000s hydro and nuclear were introduced. The energy bases have gradually expanded from the north to the center and increasingly to the west of China. Energy delivery became an issue in the late 1980s when China began its massive investment in the "West-to-East" distribution networks, and more recently (2011-2015) in moving abroad to the rest of Asia.

Table 21. Energy sector targets extracted from National Plans 1981-2015

Energy Targets	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
Production Capacity	Mining 80 million tons			Coal 140 million tons; crude oil 155 million tons			
Capacity Increase	12.9 million KWh hydro & thermal 35 million tons crude oil	65 m KW					40 million KW nuclear 290 million KW hydro 100 million KW wind 21 million KW solar
Electricity Generating Capacity			1 trillion KWh	1.4 trillion KWh			
Annual Growth (%)				7			
National-scale projects					+5 large hydro plants	30 wind projects	
Energy Base	Hydropower – Yellow & Yangtze Rivers Thermal – Shanxi, Inner Mongolia	Nuclear in the coast	Coal – north Gas – west Thermal – middle			Wind power base north & east coast Hydro base in Jinshan, Yalong & LanCang Rivers	Coal bases – Shaanxi, East Inner Mongolia, Liaoning, Yunnan etc 5 oil & gas production areas 8 wind bases
Energy Transmission and Distribution		Strengthen grid for "West-to-East" delivery			Strengthen grid for "West-to-East" delivery	Strengthen national grid	Kazakhstan oil pipeline China-Burma pipeline China-Central Asian pipeline Smart-grid pilot 200,000 km of 330 kV transmission lines
Environmental Concern			Efficiency Requirements Imposed	"Clean Development" agenda	Diversify energy portfolio		

Source: Chinese National Five-Year Plans (1981-2015)

Environmental concerns were first raised in the early 1990s when the first set of energy efficiency requirements was set. Consequently, while from 1980 to 2010 China's economy increased 18-fold, energy consumption increased only 5-fold (World Bank 2014). Energy intensity per unit of GDP declined by about 70 percent during the same period (*Ibid*). The interpretation of environmental quality became more comprehensive, focusing not just on efficiency gains, after the adoption of the "Clean Development Agenda" in the late 1990s. The agenda consists of a series of regulations and policies on pollution control and the use of market instruments such as the Clean Development Mechanism. By the end of 2010, China had already become the world's largest renewable market, investing US$89.5 billion in 2014 – 73% more than the US, the next largest investor (The Climate Group 2015). By the end of 2012, China had hosted nearly half of the CDM projects developed globally and almost all the CDM projects associated with coal mine methane (ICMM in Uddin *et al*. 2015).

Electricity supply, transmission and distribution

Governance of the electricity system in China has gone through a series of reforms, with market forces playing progressively more important roles (Bai & Qian 2010). Before 1978, the system was centrally planned under a number of different agencies such as the Ministry of Electricity Industry and Ministry of Coal Industry (see Figure 46) (Andrews-Speed et al. 2010).

A major landmark in reform occurred in 2002, when the State Council issued the System Reform Plan for the Electricity Sector. Notably, electricity generation was separated from its transmission and distribution as well as its other businesses. The National Electric Power Corporation was divided into regional power grid companies whereby each is a monopoly transmitter, distributor, and retailer of electricity in its region. During this period, central and local governments and private/foreign investors controlled about 54%, 40% and 6% of installed capacity respectively (Bai & Qian 2010).

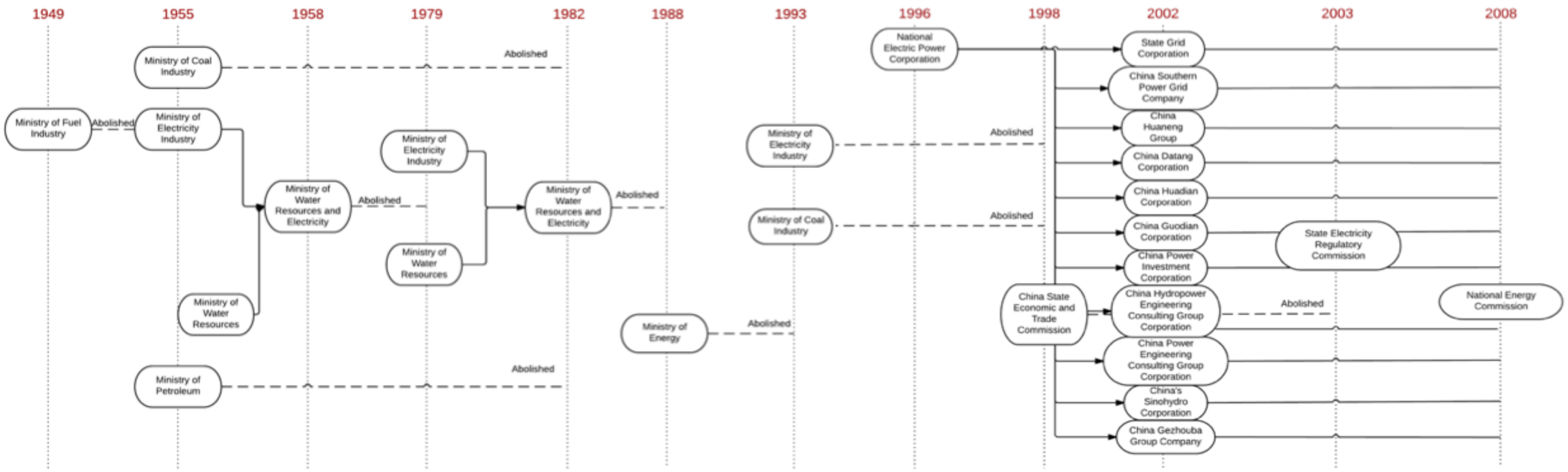


Figure 46. Institutional Evolution of the Energy Sector 1949-2008.

Source: authors' interpretation, adapted from Zhang (2009).

Spatially, Figure 47 shows that the number of power plants has grown exponentially – 22 times between 1969 and 2014. The growth has been particularly rapid over the last 20 years (between 1998 and 2014) and has tended to concentrate on major industrial centers along the coast and around cities. Some power plants have been shut down because of environmental regulation, although more have expanded their capacities since they were first constructed.

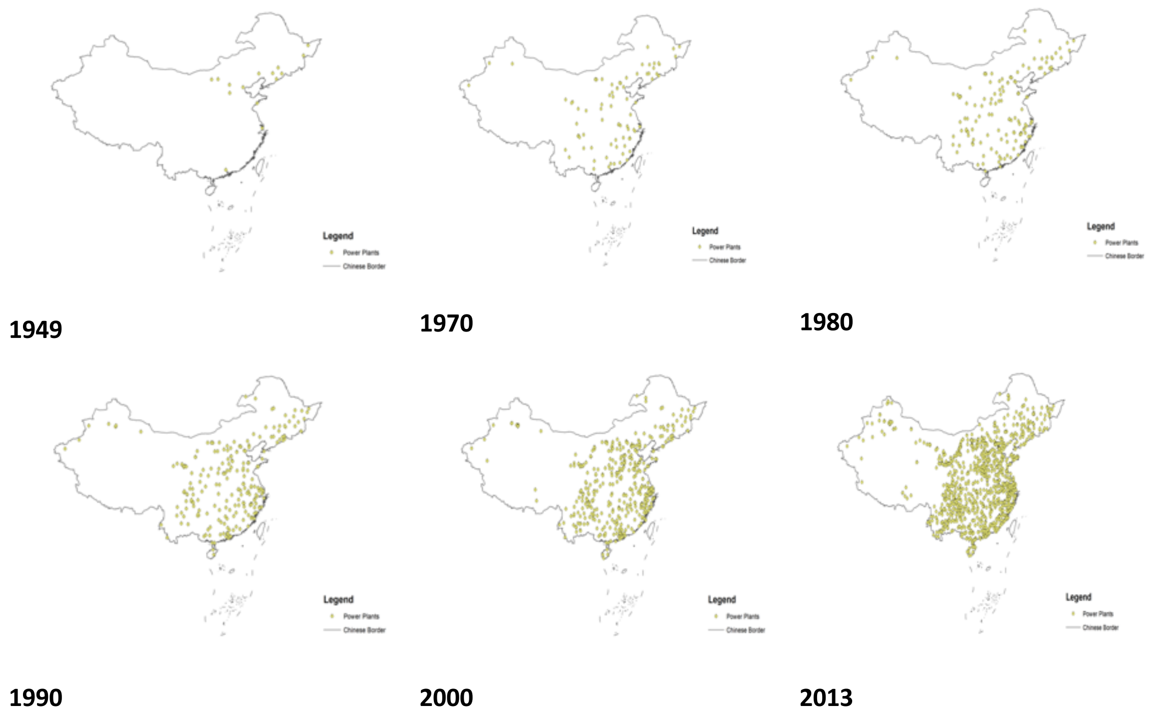


Figure 47. Spatial development of electric power plants.

Source: authors' own data and analysis.

Transport

Development of the transport sector can be split into two phases (Table 22), the first being a strategy of increasing the number of assets and the second being a more systematic approach involving the development of networks such as national trunk roads. By the end of 2015, the strategic "five vertical and seven horizontal" road network that stretches across the country; the "four vertical and four horizontal" rail network, the world’s most extensive high-speed rail network; and an extensive motorway network had been formed (see Figure 48). Currently, the Chinese government is preparing to build an integrated urban intercity rail network and 42 integrated transport hubs.

Table 22. Transport sector targets extracted from National Plans 1981-2015

Transport Targets		1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
Additional Assets	Rail (km)	2,067	3,600				17,000	
	Rail (electrified, km)	2,511	3,300					
	Rail (doublet-racked, km)	1,689	4,000					
	Highway (km)		1,600					
	Secondary roads (km)		10,000					
	Waterways (km)		5,000					
	Deep-water berths	54	120					440
	Ports						12	
Capacity Increase		100 million tons berths						
Network extent (km)						Road 1.6 million		
						Rail 75,000		
Annual Growth (%)	Rail	10.5	25.5					
	Barge cargo	16.4	23.2					
	Coastal port throughput	19.6	51.5					
	Road	20.8	38.5					
	Civil aviation	86.5	100					
National-scale projects		7 trunk roads		New “north-south”, “northwest”, “southwest” coal routes	Rail: southwest, northwest, northeast corridors for coal	Roads: “five vertical & seven horizontal network”	+ 12 highways built	+ 3 highways built
								42 integrated transport hubs
								“four vertical & four horizontal rail lines
								Urban intercity rail
								Formation 83,000km motorway
				“National trunk road” Beijing-Guangzhou; Beijing-Shanghai; Shenzhen-Harbin	Waterway: corridor linking coal, crude oil, iron ore & containerisation			

Source: Chinese National Five-Year Plans (1981-2015)

National Highways

Before 1978, highways were entirely state planned (Bai & Qian 2010). In 1981, the State Council approved the Ministry of Communications' report on the provisions of a national highway road network, which consisted of thirty-four routes, seven of which radiate out of Beijing, while nine are north-south vertical lines and eighteen, east-west horizontal lines (Ministry of Transport 2009). Among these, five vertical and seven horizontal lines formed the “National Motorway System” (left, Figure 48). In 2000, additional routes were added owing to China’s newly announced “Western Campaign”, which included the construction of “eight major motorways across Western China” (middle green lines, Figure 48). In 2005, the Chinese National Highway Plan was launched that complemented the “five vertical and seven horizontal lines” and “eight major motorways” (right, Figure 48).

1990 2001 2005

Figure 48. Spatial evolution of China’s highway network.

Source: adapted from Ministry of Transport (2009).

Rail

Prior to 1949, China’s railway network was concentrated in the north and north-east of the country (see Figure 49). In the 1950s, the Chinese central government was the sole investor, owner, operator, and manager of the railway system. In the first Five-Year Plan (1953–1957), over 60% of the infrastructural investment (9.015 billion RMB) was used for railway construction (*Ibid*), concentrated in the raw-materials-rich north. In the 1960s, expansion inland commenced as a result of the breakdown of diplomatic relations with the Soviet Union.

1949 2000 2014

Figure 49. Spatial evolution of China’s railway network.

Source: data from Wang et al (2009); OpenStreetMap Contributors (2014).

From 1978, China began its “Open Door Policy”. In the 1980s and 1990s, many new “corridors” (e.g. South-west, North-South, North-East) were constructed to transport coal and other goods from the north to the south/east coast to stimulate economic development. Meanwhile, much of the old network was electrified and upgraded. From the 2000s, the structure of “eight vertical and eight horizontal networks” emerged (see Figure 49). The Qinghai-Tibet high-speed railway – the world’s longest and highest altitude railway – was built in 2001, connecting the inland with western China for the first time. By 2005, the ninth Five-Year Plan included as a target 75,000 km of operating railway (National Development and Reform Commission 1996). In the tenth Five-Year Plan, urban intercity rail lines became a new focus: cities with a population of over 500,000 were to be connected by high-speed rail (National Development and Reform Commission 2001a).

Aviation

By 1949, there were 31 airports, quite widely spread across the country (see Figure 50). All would have been managed by the Civil Aviation Administration (CAAC) under military supervision (Shaw et al. 2009). Air transportation, which mainly served people who worked for government agencies or state-owned enterprises, experienced huge losses.

1949 **1970** **1980**

1990 **2000** **2013**

Figure 50. Spatial development of airports in China.

Source: authors' own data and analysis.

In 1978, market-based reforms began. The CAAC was separated from the military, made responsible for losses incurred and allowed to retain part of its revenues (*Ibid*); some airports, albeit a limited number, began to be managed by local governments (Yang et al. 2008). In 1987, the CAAC's role became solely regulatory. Its operational role was gradually passed onto six state-owned trunk airlines[19] and local governments between 1987 and 1991 (*Ibid*). Meanwhile, a number of new carriers funded by local governments or government-owned enterprises entered into the market between the mid-1980s and early 1990s. However, many of the new carriers were too small to achieve economies of scale and were losing money. In response to the deteriorating financial situation caused by competition among the airlines, the Chinese State Council released a new policy announcement in 1993 that encouraged mergers and consolidation.

Whilst in 1994 only 78.6 million passengers and 0.91 million tons of cargo were handled at the country's airports by 2006, these figures had risen to 332 million and 7.5 million, respectively – amounting to average annual growth rates of 14.2% and 21.5% (*Ibid*). By 2012, China's air industry had reached an air passenger volume of 319 million and an

[19] Air China, China Eastern Airlines, China Southern Airlines, China Southwest Airlines, China Northwest Airlines, and China Northern Airlines

air passenger movement of 502.6 billion person-km with 180 commercial airports in service. The scale of the sector is only surpassed by the USA (Wang et al. 2014).

Water supply, irrigation and flood control

Water resource management strategies in China have been supply-side focused and concentrated on large-scale projects (see Table 23), focusing upon water supply, irrigation and flood control. National projects such as the North-South Water Transfer Project, established as early as 1986, have been undertaken to deal with China's water resources problems, such as flooding and drought.

Table 23. Water sector targets extracted from National Plans 1981-2015

	Water Targets	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
Water Supply	Urban water coverage (%)				96			
	Rural water coverage (%)				42			
	Rural clean water supply						100 million rural residents access	
	Additional supply (bn cubic metres)					40		
	Total supply (bn cubic metres)				400-500			
Flood control		Yellow, Yangtze, Huai, Hai rivers						
Irrigation		Heilongjiang, Jiangxi, Hunan and Anhui lakes						
National-scale projects			North-South Water Transfer planning	3 major water conservation projects: Xiaolangdi, Wanjiazhai, Yellow River Diversion Project		Dike construction in Yangtze, Yellow rivers	North-South Water Transfer planning intensified	North-South transfer: eastern/middle lines completed
								Drinking water project in Guizhou
				Assessment Three Georges Dam		+ 8 water control projects built		Canal Diversion Dajihuang-Qinghai
								7 reservoirs built

Source: Chinese National Five-Year Plans (1981-2015)

Seven major river basin and watershed management committees were set up to plan water infrastructure assets within their respective basins; these included Water Resources Committees for the Yellow River, Yangtze River, Pearl River, Haihe River, Huaihe River, Songhua/Liao Rivers, and Taihu Basin (Cao 2010). Before 1949, the country only had 23 large/medium-sized reservoirs (Liu & Zhang 1999). After that, 84,000 were built, among which 412 are large, while 2,634 are medium-sized (*Ibid*). Figure 51 shows the construction boom in the 1960s and 1970s.

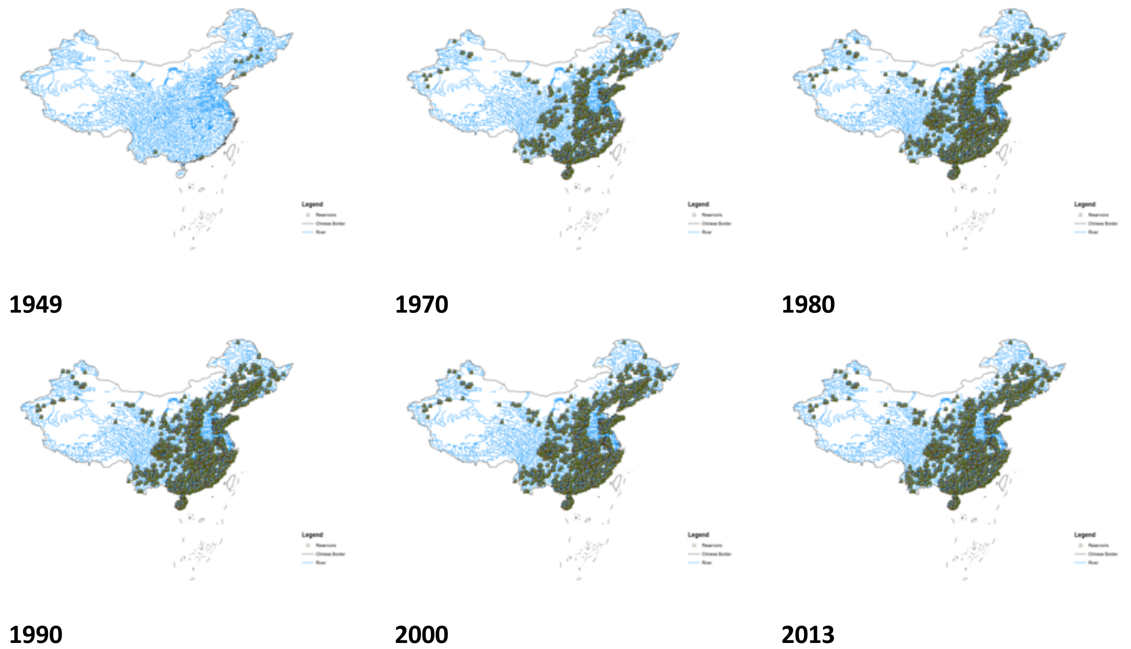


Figure 51. Spatial development of reservoirs in China.

Source: authors' own data and analysis.

Despite efforts to manage water resources, China faces complex challenges with ageing water infrastructure, pollution, and the increasing demand for water. Sedimentation has rendered many reservoirs ineffective. In fact, more than 46,000 of the 87,000 dams and reservoirs built since the 1950s have surpassed their life spans, or will within the next 10 years, which will increase the risk of structural failure (Liu & Wu 2012). In addition, although the rate of growth in water use has slowed from 1.46 percent in the 1990s to 0.6 percent in 2010, there are concerns that China's water demand will continue to increase as its population peaks around 2030 (Global Water Partnership 2015).

To address the complex challenges, in 2011 the central government set about major reforms to implement stringent water resource management and set up "three red lines" to control total water use, improve water use efficiency, and control water pollution (*Ibid*). The new approach reflects a shift from supply to demand management and emphasizes the importance of integrated management strategy to ensure environmental protection and sustainable development (*Ibid*). Nonetheless, supply-side targets such as having the “total reservoir capacity of the country … reach 25% of [the] annual flow of rivers” are still in place (National Development and Reform Commission 2009).

Sewage and solid waste

Before the 1950s, urban sewage treatment virtually did not exist and wastewater treatment focused on farmlands in the 1960s. In the 1970s, cities relied on “stabilization ponds” for the removal of suspended solids, organic matter and other pathogens. By the end of the 70s, some 38 stabilization ponds had been built for treating domestic (50%) and industrial waste (50%) (Liu 2014). From the beginning of the 1980s, the national government permitted the use of preferential loans from international organizations, governments and equipment suppliers under a “city government guarantee repayment” scheme. This scheme ensured loan repayments from city governments and promoted a construction wave of urban wastewater treatment plants, the first of which was the successful installation of a plant in Tianjin in 1984 (*Ibid*). During the ninth Five-Year Plan period (1995-1999), China launched the "Three Rivers" (Huaihe, Haihe and Liaohe), "Three Lakes" (Taihu, Chaohu, Dianchi) and the "Bohai" regional water pollution control whereby an additional 22 wastewater treatment plants were built with state funding (*Ibid*).

By 2000, 427 municipal sewage treatment plants had been built (Yu et al. 2004). However, China's urban sewage treatment rate remained low, at less than 20% in 2004 (*Ibid*). Table 24 shows that waste processing is a recent development phenomena and increases towards the 2000s. Targets appeared only in the late 1990s and only urban sewage has had a consistent target since then.

Table 24. Waste sector targets extracted from National Plans 1981-2015

Waste Targets	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
Industrial wastewater treatment (%)				83			
Sewage treatment (%)							
Waste gas treatment (%)				86			
Solid waste re-utilisation (%)				50			
Urban sewage treatment (%)				25	45	70	85
Non-harmful refuse treatment (%)				50			80

Source: Chinese National Five-Year Plans (1981-2015)

Rapid progress kicked off in 2006 and by 2010 the coverage of urban sewage treatment facilities had increased by 32% – from 62.2% to 92.8% (Ministry of Housing and Urban-Rural Development 2010). This is equivalent to 246 million and 372 million households' waste being treated in 2006 and 2010 respectively[20]. During the same period, the national urban sewer length increased by 64%, reaching 478,000 km (*Ibid*). As of 2010, national daily urban sewage treatment capacity reached 125 million cubic meters per day; by 2015 it was expected to reach 170 million cubic meters, becoming the world's largest (*Ibid*). Figure 52 demonstrates the exact growth pattern: virtually no waste treatment existed in our database before the 1990s. The number of waste treatment facilities in 1991 was 34; in 2001 it increased to 184, and by 2011 China had 2,740 plants. The "golden decade" for the waste sector was the 2000s, when the number of assets rose 14 times. Most are located in urban areas along the coast, and in the center and south of the country.

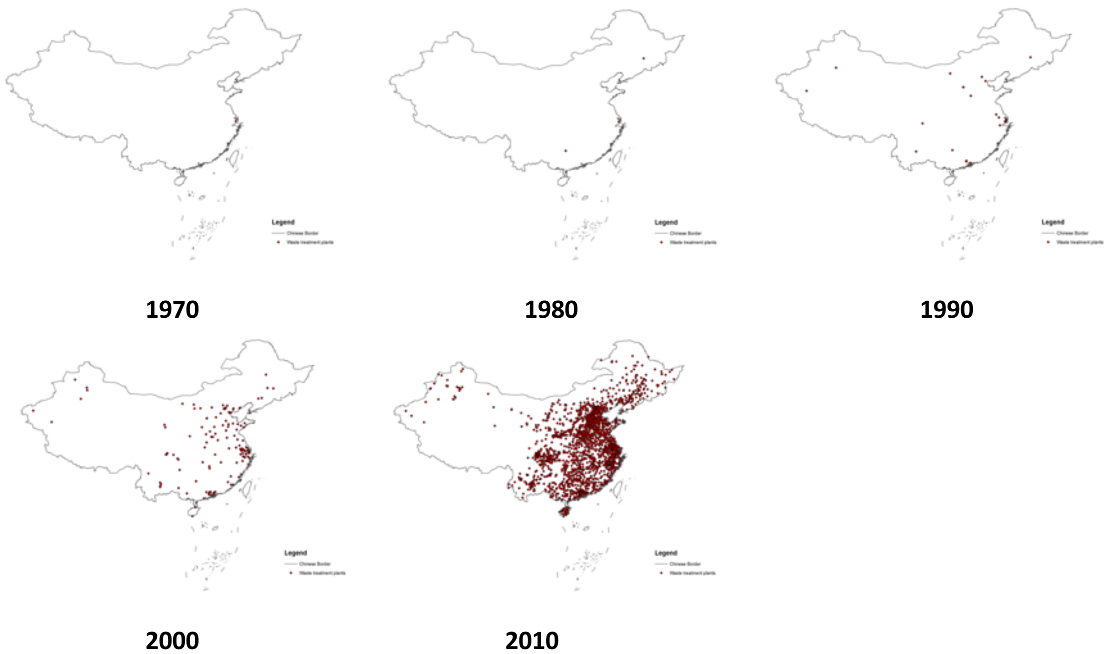


Figure 52. Spatial development of wastewater treatment plants.

Source: authors' own data and analysis.

[20] Number of households calculated by the 2005 and 2010 census (National Bureau of Statistics of China 2006; National Bureau of Statistics of China 2011). 2005 was chosen instead of 2006 as an estimate, because we do not have data for 2006.

The 12th Five-Year Plan has set a number of pollution targets – cuts to ammonia levels for the first time, alongside cuts in chemical levels of nitrous oxides, Sulphur dioxides and chemical oxygen demand (KPMG 2013). By 2015, the national urban sewage treatment rate was projected to reach an average of 85% of all discharges, with municipalities, provincial capitals and designated city districts expected to achieve 100%; prefecture-level cities to achieve 85%; and county-level cities to achieve 70%. The county sewage treatment rate is to reach 70% on average, and townships, 30% (China State Council 2012).

The management and financing of wastewater treatment systems (except for a few national-scale plants), unlike the other infrastructure sectors, have always been the responsibility of municipal governments (see Figure 53 for an explanation of the approval process for a wastewater treatment plant). Central government, on the other hand, has played a relatively small role, except for the pollution control policies for the "Three Rivers" in the late 1990s.

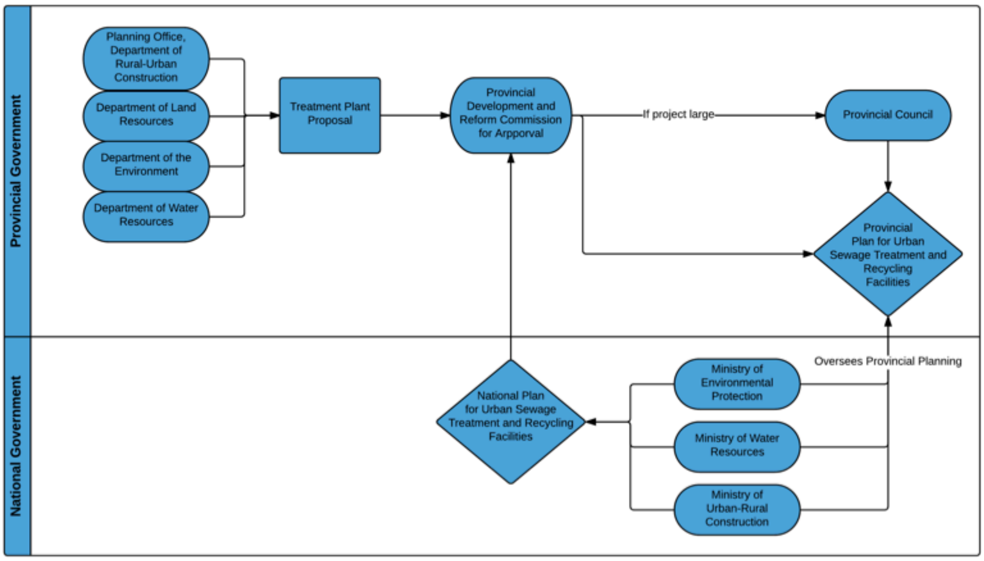


Figure 53. Wastewater Approval Process.

Source: authors' interpretation after numerous interviews with relevant policy makers.

Digital communication

As in many countries, digital communications (including fixed, mobile and satellite communications) developed rather late, but boomed. In the 1990s, the sector expanded at four times the global average, and China is now the largest telephone user and second largest Internet user in the world (Heshmati & Yang 2006). By the end of 2006, fixed-line telephone subscribers had reached 367 million (28% of total population[21]), an increase of 172 times compared to 1980, and the average annual growth rate of the communications industry has been sustained at an impressive 20% with most years exceeding the GDP growth rate by 2.5 times (Ministry of Science and Technology of China 2008). Rural digital infrastructure continued to rise steadily. Villages with broadband connection increased to 87.9% (China Information Centre 2014). China's big data market has emerged and its marked size reached 450 million RMB in 2013 (*Ibid*).

Examining the national plans, it would seem that the extraordinary growth in China's digital communications sector, in contrast to other infrastructure sectors described above, has not been led by the state (see Table 25). However, the state has played a significant role in the development of digital communication by establishing a national information network system consisting of hundreds of projects. The most notable are the "Twelve Golden Projects": including the digitalization of information on taxation, trade, fiscal budgeting, e-commerce, auditing, public security, insurance, water resources, rural communities, quality supervision, tourism, public health, land resources, all initiated at national level at the beginning of the 1990s (China State Council 2002; National Planning Commission 2012).

[21] Calculated from the 2005 census (National Bureau of Statistics of China 2006). 2005 was chosen instead of 2006 as an estimate, because we do not have data for 2006.

Table 25. Digital communications targets extracted from National Plans 1981-2015

ICT Targets	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
Optical fibre networks			Focus in Beijing, Tianjin, Shanghai 8000 km optical cables	Reach 210,000 km optical cables			
Telephone penetration (%)			2				
Telephone exchange centres			15 million				
Additional Long-distance telephone circuits			150,000				
Additional digital program-controlled switches			8.6 million lines				
Additional micro-computers			300,000				
Additional colour-TV			12 million				

Source: Chinese National Five-Year Plans (1981-2015)

In 2015, national efforts to improve information technology became ever more prominent. During the "Twelve Five-Year" period (2011-2015), between five and eight large enterprises worth more than 500 billion RMB of sales were to be formed (Ministry of Industry and Information Technology 2011), China’s Broadband Strategy requires basic coverage in urban and rural areas by 2020. Fixed broadband subscribers are projected to reach 400 million, with 70% household penetration; 3G / LTE users are to reach more than 1.2 billion with a user penetration rate of 85% (China State Council 2013).

Our analysis of government policies and plans demonstrates the central role that government has played in China’s infrastructure development – more so than in countries where decision making is less centralized or structured and more strongly governed by market forces. However, parts of the economy cannot be planned for or controlled. It has often been the case, especially since China opened up, that its economy has grown more than expected. This has resulted in shortages in infrastructure supply as planning has been central to service provision. In other cases, oversupply has led to wasteful investment, as in the case of the “ghost towns” across China. Recognizing the shortcomings of a planned economy, the on-going reforms are increasingly letting the market allocate resources, and infrastructure supply is being driven by “organic” demand, which is a function of economic and population dynamics. Historically however, the Chinese government has intervened in times of crisis. In fact, the reason behind the acceleration of construction efforts in 1998 was that highway construction became part of the government’s stimulus spending after the Asian financial crisis (Asian Development Bank 2007, in Faber 2014). Overall, infrastructure planning will increasingly be allocated via the market, although intervention from the state is expected in times of difficulties and to address broader political and security objectives.

8.5. Infrastructure development framework in China: a synthesis

Based on the discussion above, we summarize a series of endogenous and exogenous processes through which multiple factors – economic, social and political – at different levels of government interplay in infrastructure development in China (Figure 54). Endogenous processes, which include changes in demographics, migration, urbanization, industrialization and economic growth, are constrained by geographical factors that dictate access to natural resources and trade. Infrastructure demand then influences supply, primarily through government planning at various municipal levels and increasingly through market mechanisms. Over time, demand and supply alter depending on the relative magnitude of these processes.

Exogenous processes, on the other hand, modify the endogenous processes. Migration, an endogenous process in most countries, is controlled by the government-dictated Hukou system (see Section 8.3) and in turn affects infrastructure demand. Government planning of infrastructure aims to achieve a range of policy objectives, including economic integration and regional development. Western China would not have been developed without government intervention. In addition, the Chinese government has launched several national and local initiatives to promote geographical integration and provided substantial economic stimulus packages to encourage infrastructure growth, leading to the uneven geographical spread of infrastructure assets. Further, foreign donors such as the World Bank and Asian Development Bank have played an instrumental role in funding infrastructure investment, especially during the early 1990s when China opened up. Exogenous disruptions come in the form of environmental disasters, including floods and earthquakes, which have destroyed stocks of infrastructure, necessitating the development of new protective infrastructure.

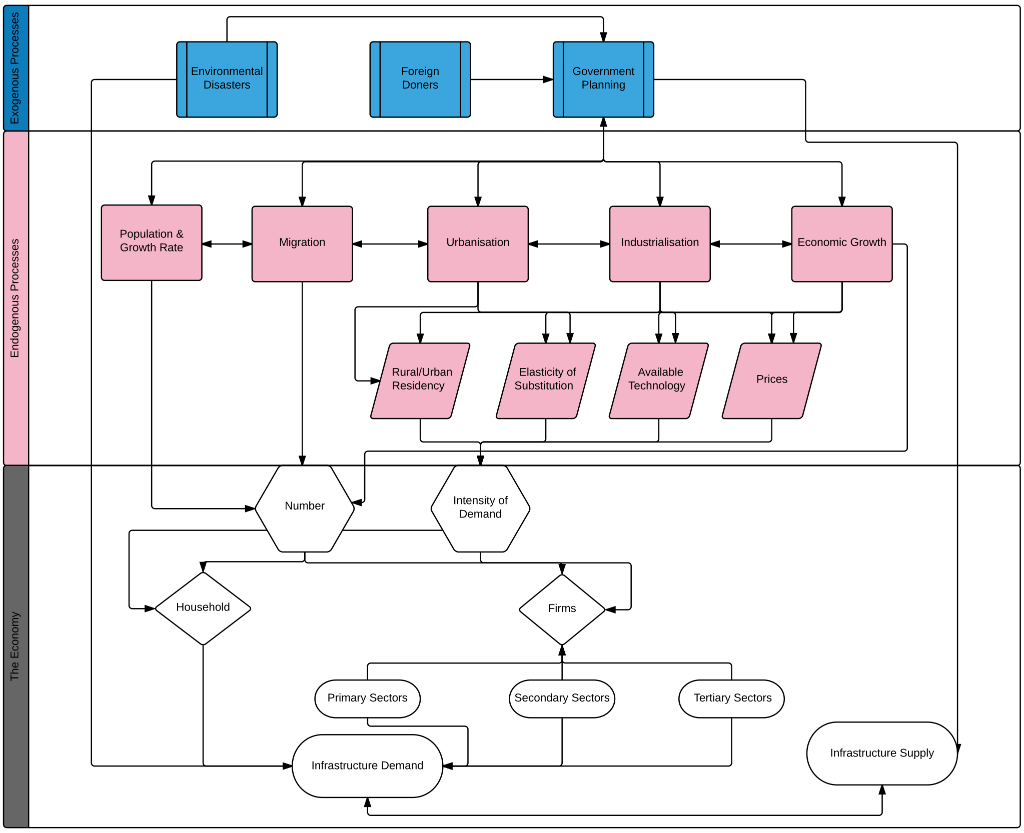


Figure 54. Infrastructure development framework in China.

Infrastructure demand is affected by firms (primary, secondary and tertiary sectors) and household demand. Its magnitude is dependent on the number of households and firms and the intensity of their demand. The number of households and firms is influenced by some endogenous processes such as demographic changes and economic growth. The intensity of the demand by households and firms is altered by urbanization, industrialization and economic processes via numerous factors such as elasticity of substitution and available technology. Exogenous processes such as government planning can change endogenous processes via state planning, which in turn affect infrastructure demand and supply.

8.6. Prospects for the future

Future infrastructure development in China will be determined by the interplay of the factors that we have discussed: changes in population, economic growth, industrialization, urbanization, migration and government planning. Whilst the interplay of these processes is complex, our analysis does shed some light on the direction in which they may develop into the future.

The Chinese government has approved its 13th Five-Year Plan (2016-2020), which aims to raise the number of middle-class citizens and focus on a transition to higher-value production capabilities. Infrastructure will play a key role in the transition to a higher-value based economy. In digital communication, for example, it is envisioned that urban areas will achieve extensive optic network coverage and 98% of administrative villages in the rural areas will have access. Transport infrastructure will improve the connectivity between the north and south; the east and west, focusing on access from Tibet into inland regions; and for intercity and urban/rural railways. Renewable energy, such as wind, photovoltaic and hydropower, will continue to be promoted. Nuclear capacity will reach 58 GW. Large irrigation facilities are to be completed and there will be advancement along the middle route of the north-south water transfer project across more than 10 regions. City and county sewage treatment rates are to reach 95% and 85% respectively.

These ambitious plans will help to address the growing demands of the urban middle class. There is an increasing emphasis on market reform. Thus, the endogenous processes that we have identified may have a growing effect on shaping China's infrastructure development in future.

The slow-down in the Chinese economy is reflected in the 13th Five-Year Plan (2016-2020), which sets an annual growth target at greater than 6.5% (Xinhua News 2016). Despite the slowdown, capital accumulation will still remain one of the main contributors to growth for a long time to come. Further, given its increasing connectivity with the world, as demonstrated by the establishment of the Asian Infrastructure Investment Bank and the

“One Belt One Road” Project, China’s future economy will depend on how the rest of the world performs.

Relaxation of the “one-child policy”, which successfully reduced China’s population growth rate in the 1980s, is expected to marginally increase the fertility rate in the short term. However, this effect is likely to be counteracted by advances in education, improvements in the position of women, and reductions in mortality (Peng 2011). Overall, most projections agree that China’s population will continue to grow for at least another decade, beyond which point uncertainties in regional differences, women’s attitudes towards having children, and household income increases make projections difficult.

Relaxation of the Hukou system, motivated by human rights concerns or shortages of migrant workers, would enable more migration (Chan 2013). In that case migration patterns will be more purely influenced by migrants’ expectations of improving quality of life. Economic development in rural areas may reduce the push-factors that motivate migration.

The way in which urbanization develops in the future will be guided by the New National Urban Plan 2014-2020 (*Guojia Xin Chengzhenhua Jihua*), which outlines a number of specific targets: for instance, the percentage of urban citizens is to reach 60% by 2020, and the percentage of motorized public transport travel is to reach 50% in cities with populations of more than 1 million (18th National Congress of China 2014). Figure 55 is the “schematic of urbanization strategy” that highlights 21 major targeted urban areas across China and shows how infrastructure projects will focus on integrating these areas and enhancing services within these regions.

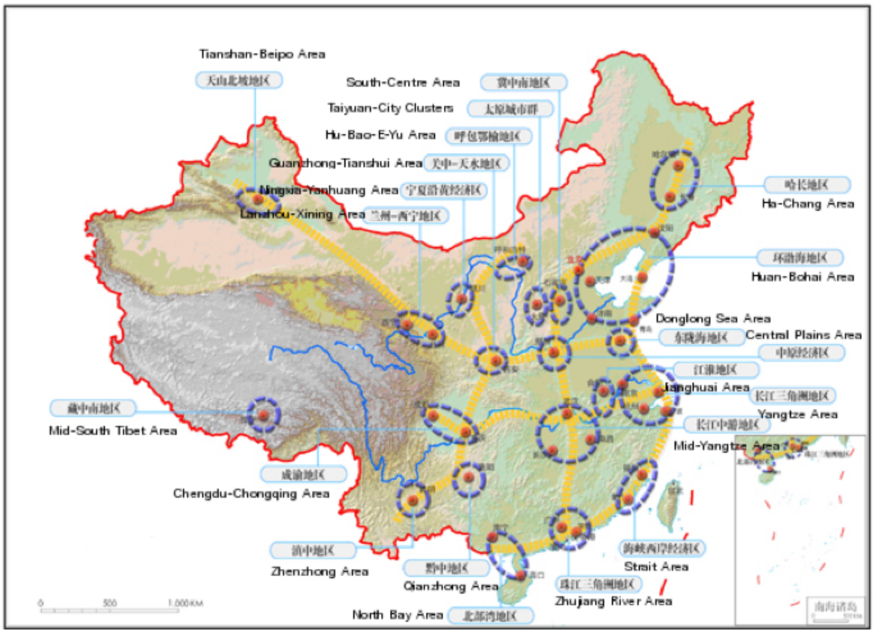


Figure 55. Future prospects for China's infrastructure development.

Source: the 18th National Congress of China (2014).

8.7. Conclusions

This paper has analyzed how the modern Chinese infrastructure system, consisting of energy, transport, water, waste and digital communication sectors, evolved over the period 1900 to 2014, with a focus on infrastructure development since the formation of the People's Republic of China in 1949. We have demonstrated how infrastructure development in China is driven by the endogenous and exogenous processes of economic geography.

Population growth and migration have driven demand for infrastructure services, particularly in urban areas. Export-led economic development has resulted in a proliferation of infrastructure in the east of the country. Nonetheless, the pattern of infrastructure development in China is not what one would expect purely on the basis of these endogenous factors, – as might be predicted, for example, by a model of economic geography. This is because of the noteworthy role of government planning and regulation. Regulation of migration has to some extent limited the rise of urban populations. The Chinese government has promoted infrastructure investment as a means of stimulating economic growth, in particular in response to the Asian crisis and the global financial crisis. The government has deliberately promoted infrastructure development in the west of China and other remote regions to encourage economic integration. Security objectives have locked in a wider geographical distribution of airports than might otherwise be expected. Government environmental objectives have shaped the development of energy and waste water treatment infrastructure over the last decade.

At times, there has been a mismatch between intended planning outcomes and reality; there were periods during which time China’s infrastructure investment was insufficient to meet demand, whilst at other times there has been an over-supply of infrastructure. Increasingly, we expect the market to become a more important factor in determining infrastructure development patterns. This is not only because China has introduced many market-based reforms in virtually all infrastructure sectors, but also due to its integration into the world economy.

9. Conclusions

9.1. Summary of findings

It is recognised that infrastructure and economic vulnerability to natural hazards, both at present and in future climates, is a huge challenge in China. Yet little is known about the nature and extent of this vulnerability and how it may change over time. This research has taken a first step towards understanding the current and future exposure of Chinese infrastructures to flooding and drought hazards by incorporating climate change scenarios. In addition, it assessed some of the economic impacts of natural hazards on Chinese businesses and industries, using flooding as a case study.

The research has focused on three main components: infrastructure modelling, hazard modelling, and economic impact modelling in order to answer the following questions:

1. How is the Chinese infrastructures system spatially exposed to flooding and drought hazards (chapters 4 & 5)?
2. What are the impacts (direct and indirect) of flooding on Chinese businesses, industries and the economy? How are infrastructure sectors affected (chapter 6)?
3. How will these impacts change in the future in the context of climate change (chapters 7 & 8)?

Chapter 4 demonstrated a conceptual framework for understanding the infrastructure system in China and provided a nation-wide spatial distribution of infrastructure assets and networks in five sectors (energy, water, waste, transport and digital communication). Not only did it examine direct exposure of infrastructure assets to flooding hazard; it also investigated the potential for indirect damage and disruption, by estimating the numbers of people indirectly dependent on infrastructure assets and pinpointing locations where critical assets are concentrated in floodplains for the rail and electricity sectors. Building on this work with improved data on infrastructure and hazard models, we extended the analysis to other transport and waste sectors for both flood and drought hazards. We found that infrastructure assets in Anhui, Beijing, Guangdong, Hebei, Henan, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang – and their 66 cities – are exceptionally exposed to flooding, which affects sub-sectors including rail, aviation, shipping, electricity, and wastewater. The average number of infrastructure users who could be disrupted by the impacts of flooding on these sectors stands at 103 million. The most exposed sub-sectors are electricity and wastewater (20% and 14 % of the total, respectively). For drought hazard, we restricted our work to the electricity sub-sector, which is potentially exposed to water shortages at hydro-electric power plants and cooling water shortages at thermoelectric power plants, where the number of highly exposed users is 6 million. Spatially, we demonstrated that the southern border of Inner Mongolia, Shandong, Shanxi, Hebei, north Henan, Beijing, Tianjin, south-west of Jiangsu – and their 99 cities—are especially exposed.

Chapter 6 examined the economic impacts of flooding on Chinese businesses, industries and the broader economy. It combined a detailed firm-level econometric analysis of 162,830 firms with a macroeconomic input-output model to estimate flood impacts on China's manufacturing sector over the period 2003–2010. We found that flooding on average reduces firm output by 3.18%–3.87% per year and its propagating effects on the Chinese macroeconomic system to be a 1.38%–1.68% annual loss in total direct and indirect output, which amounts to 17,323–21,082 RMB billion. Lagged flood effects over the following year were estimated to be a further 1.73% at firm level and 0.75% or 9225 RMB billion at the macro-level. In terms of economic sectors, we observed that within the whole Chinese manufacturing sector, industries such as chemical and metal smelting and rolling processing suffer the highest losses at 2,690 and 2,693 billion respectively. Out of the other non-manufacturing sectors we observed significant indirect impacts on agriculture, oil and gas, and key infrastructure sectors such as the electricity, heat production and supply industry, the gas production and supply, the water production and supply industry, the building industry, the transportation and warehousing industry, the information transmission, computer services and software industry.

Chapter 7 investigated the effects of climate change on flooding risks by driving a global river global river routing (CaMa-Flood) model, using the daily runoff of 11 Atmospheric and Oceanic General Circulation Models (AOGCMs). It analysed how the Chinese infrastructure stock, comprised of a total of 60,916 assets, including the energy, water, transport, waste and digital communication sectors, will face changing flood probabilities, and estimates the number of customers potentially affected. By 2055, the number of infrastructure assets exposed to increasing probability of flooding under RCP 4.5 were found to be 41, 268, 115, 53, 739, 1098 and 432 for airports, dams, data centres, ports, power plants, rail stations, and reservoirs respectively – almost 8% of all assets for each sector. The lengths of line assets exposed to increasing flood hazards were found to be 14,376 km, 32,740 km, 102,877 km and 25,310 km oil pipelines, rail tracks, roads and transmission lines respectively. Under RCP 8.4, the numbers increased to 51, 301, 137, 71, 812, 1066, 424 for point assets. Linear assets increased to 19,938 km, 39,859 km, 122,155 km and 30,861 km. The average number of customers affected by increasing flood probabilities were 54 million, 114 million and 131 million for airports, power plants and stations respectively. However, within this aggregate increase there was large spatial variation, which has implications for the spatial planning of adaptation to flood risk to infrastructure.

Chapter 8 studied the ways in which infrastructure stocks may evolve into the future by looking for lessons from the past. It built a framework that identifies the drivers of infrastructure development in China using evidence from policy documents and a unique geospatial dataset for the years 1900–2010. We have interpreted the interplay between economic demand-driven factors and state-led interventions in the context of strong path-dependency in infrastructure systems. Prior to 1949, China inherited infrastructure primarily in the rail and power sectors. Between 1949 and 1979, its construction efforts were focused in the water sector, and the number of reservoirs increased by 134%. After China opened up to international trade in the 1980s, investment in transport, energy and digital communications soared. Coastal regions led trade-based economic growth and consequently were foci for infrastructure development, which reinforced the benefits of agglomeration. However, this regional economic geography phenomenon has been accompanied by government policy deliberately targeting the west of the country and more isolated regions for economic development. Local governments became more involved in infrastructure investment after the 1994 reform, whilst national government shifted its attention to improving inter-regional connectivity. The interplay between the processes that we identified will determine how infrastructure continues to evolve in China in future.

9.2. Research contribution

This research has contributed to knowledge about Chinese vulnerability to climate change impacts. Nationwide studies on how China is vulnerable to flooding and droughts are very rare in the Western scholarly literature. Within China, the latest national climate change impact assessment and numerous other government efforts have studied extensively how flooding and drought may affect the country. Yet few have achieved the spatial resolution presented in this research, incorporating climate models.

Most importantly, very few have looked at how these hazards are related to the infrastructure system, despite its vital role in guaranteeing energy and water supplies, and in sustaining the economy. This work has built an infrastructure exposure map of China across multiple sectors and locations for the first time. Further, the study not only provided an inventory of infrastructure assets, but also sought to quantify the potential scale of disruption due to infrastructure failure. It developed a new metric for estimating the number of exposed populations who might be vulnerable to natural hazards because they are either directly or indirectly dependent on the infrastructure assets concerned, which helps us compare vulnerability across different infrastructure sectors from a systems perspective, despite the fact that the nature of disruption can vary among sectors. This approach could be used to study other natural disasters that are common in China, such as snowstorms and landslides.

Further, potential indirect impacts were also studied by an empirical piece of work on the impact of flooding on the manufacturing sector and its associated potential indirect impact via input-output analysis. It is one of the first-ever empirical studies of natural disaster impact at firm-level, providing some much-needed quantitative evidence on climate-induced impacts in China. It is also a novel attempt to link firm-level results with macroeconomic analysis to estimate natural disaster impacts in China. In particular, we demonstrated how the interdependency of different sectors could result in losses from one sector to the next and provided evidence as to which sector might be affected the most. In addition, this work demonstrated that interdependency is not only linked with sectors, but also with time. Many business analysts believe the impact of flooding on manufacturing companies is short-lived and that they normally bounce back after the event. We hereby provided contrary evidence that post disaster, the financial losses for firms can still be significant.

Lastly, we examined how China's infrastructure may evolve into the future by studying lessons from the past. We built one of the first ever time series database on China's infrastructure growth, based on individual assets and networks. Understanding these drivers – population dynamics, economic growth, government planning – provides a useful foundation for future research, which could be used for developing infrastructure models that project the locations of future infrastructure assets and networks in China, thereby quantifying China's changing infrastructures exposure and vulnerability over time.

9.3. Limitations and future research

Although this piece of work represents one of the first steps in addressing a complex problem that is not well understood, it does have several limitations. On the hazard and climate side, hydrological data at the national level are not as comprehensive as one expects. This is especially true for drought. Even though the Cama-Flood model does provide high-resolution modelling results from complex hydrological processes and data, it is a river-based model and excludes pluvial (surface) and coastal flooding, which can be important for infrastructure exposure analysis. Therefore, an important aspect of future research should be addressing higher resolution data access for both flooding and drought hazards. This could include using better digital elevation models, more advanced soil and evaporation models, and incorporating flood data on pluvial and coastal flooding events. As for the validation of flooding, which is always challenging, is partial in this thesis, one could improve this work and make use of the historical remote sensing images that have recently become available. These are at high resolution and go back to the 1990s and can be used for validating smaller-scale events. This would have also allowed us to improve the precision of the geo-location of affected firms in the impact paper as the resolution of recorded floods we used in this research was at city scale. Future projections of climate-induced hazards inevitably come with uncertainty thus we should explore a wider range of scenarios from a variety of climate models and not just focus on the Cama-Flood model. Other models that could be incorporated are GLORIS as applied in Ward *et al*'s paper (Ward et al. 2017). Further, future work should look into flash floods and other types of natural disasters which have been increasing in both number and magnitude.

On the infrastructure side, data can be improved, especially the locations of assets and networks which are important for understanding exposure. This is especially true of ports and data centres, for which better data would have enabled us to estimate the impact of climate induced hazards more accurately. In addition, one needs to study the role of flood defences which were not fully incorporated in this research. This includes a better understanding of physical vulnerabilities at the local level, for example, what local protection and drainage system are in the areas concerned; what the elevation standards are for power plants and other assets etc. It is now possible to do that with the newly introduced flood control legislation which details the flood protection level for different types of infrastructure assets. Only by considering the flood protection levels for individual infrastructure assets can we study exposure and changing exposure properly. Further, this research also calls for more data on infrastructures. The modelling results from this research may not show all infrastructure hot spots because in some cases, we have incomplete data sets on infrastructure assets. Therefore, the results presented may be an underestimate of infrastructure exposure and vulnerability. More data would have allowed us to capture interprovincial electricity transfer for our electricity "hotspot" analysis, as we did not have data on national-scale transmission networks.

Regarding the economic impact study, one limitation is that we present an average effect, but firm characteristics differ, which means that the "true" cost for an individual business might be larger or smaller depending on its size and that of the sector, which we do not examine. In addition, this is only a partial review of flood impacts, as we focus on the manufacturing sector and propagating effects on the broader economy; there would have been impacts on other sectors as well as households. Further, we are not able to incorporate the costs of capital replacement, reconstruction and replacement of damaged stocks as our measure of firm output is based on an index of revenue and labour.

Further research should incorporate business damage data, which are sometimes disclosed by large listed companies. It should also look into the actual mechanisms by which businesses are affected, either direct capital damage or indirect interruptions or perhaps a combination of both. One should pay particular attention to supply chain – as we demonstrated being located in areas where there have been large floods could have a significant cost for firms, not only those in the affected regions but also much more broadly. As such, it is crucial for us to study how sectors and ultimately firms are related, for instance, when and where are the supply side constraints, how supply chains are reallocated within the input output model, what are the priorities within the supply chain which all affect how quickly businesses can recover from a natural disaster. Moreover, labour effects can be a crucial mechanism by which businesses are affected. As such, future work should understand the dynamics of labour effects such as how labour may not be able to travel from outside the floodplain (and for how long).

Lastly, it is of regret that this thesis was unable to implement a future infrastructure model based on the set of drivers developed in chapter 8. Future work could develop a spatial infrastructure allocation model which is built on these drivers. Such a model could be built on principles of new economic geography models whereby China is divided into regions with a set of initial economic conditions, given a fixed level of infrastructure stock. Each of these regions would comprise of economic sectors with a set of labour available. We could introduce some of the drivers we identify in chapter 8 to this model, giving particular consideration to government planning which has been arguably one of the most important drivers for infrastructure development in China. Infrastructure demand and supply will change as the agglomeration forces evolve. Another way to build such a model is from the supply side. It is now possible to obtain data on natural resource basins in China (energy, water) and one could establish and quantify the linkages between these resource basins to where future infrastructures are built, based on some physical constraints. For instance, sites for coal-fired power plants will depend on a set of sophisticated rules such as proximity to natural resource basin, urban areas, the surrounding transport links and the amount of budget available among others. Once we allocate a set of rules for selected geographical locations of interest, this model could enable projecting locations of potential infrastructure growth, thus allowing an examination of how exposure may change over time.

Despite these limitations, this research represents significant improvement on previous studies for understanding China's vulnerability to climate change impacts. It has for the first time, examined infrastructure exposure and vulnerability with a comprehensive dataset which covered the most important infrastructure assets and networks in five key sectors (energy, water, transport, waste and digital communication). It has also applied advanced hydrological models to assess changes in climate-induced hazard probabilities, which is higher resolution than most nationally available assessments. Further, this research represents one of the first-ever studies to look at disaster impact on the Chinese economy focusing on the firm level. Whilst further work is needed, the research has deepened our understanding of the changing vulnerability of the Chinese infrastructure to climate change impacts in a systematic manner, which is important given China's rapidly industrialisation, its increasingly important global trading role, and susceptibility to climate change. The results here provide much-needed evidence on the nature and extent of vulnerability of China's infrastructure, businesses and industries to climate impacts and demonstrate the need for adaptation. Overall, the results will be useful for informing strategic and spatial infrastructure planning.

References

18th National Congress of China, 2014. *National New Urban Plan 2014-2020 (国家新型城镇化规划)*, Available at: http://politics.people.com.cn/n/2014/0317/c1001-24649809.html.

Alfieri, L. et al., 2015. Global warming increases the frequency of river floods in Europe. *Hydrology and Earth System Sciences Discussions*, pp.2247–2260.

Andrews-Speed, P., Dow, S. & Gao, Z., 2010. The Ongoing Reforms to China's Government and State Sector: The case of the energy industry. *Journal of Contemporary China*, 9(23), pp.5–20. Available at: http://www.tandfonline.com/doi/abs/10.1080/106705600112029 [Accessed October 30, 2014].

Arnell, N.W. & Gosling, S.N., 2016. The impacts of climate change on river flood risk at the global scale. *Climatic Change*, 134(3), pp.387–401.

Arvidsson, B. et al., 2015. Investigation method for cascading effects between critical infrastructures. *Safety and Reliability of Complex Engineered Systems*, pp.3399–3407.

Aschauer, D.A., 1990. Why Is Infrastructure important? *Transportation Research Board*, p.pp 21-68.

Ayyub, B.M., Braileanu, H.G. & Qureshi, N., 2012. Prediction and Impact of Sea Level Rise on Properties and Infrastructure of Washington, DC. *Risk Analysis*, 32(11), pp.1901–1918.

Bai, C.-E. & Qian, Y., 2010. Infrastructure development in China: The cases of electricity, highways, and railways. *Journal of Comparative Economics*, 38(1), pp.34–51. Available at: http://linkinghub.elsevier.com/retrieve/pii/S014759670900081X [Accessed July 10, 2014].

Baiardi, F. & Corò, F., 2013. GVScan: Scanning Networks for Global Vulnerabilities. In *2013 Eighth International Conference on Availability, Reliability and Security (ARES)*. Regensburg. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6657304 [Accessed February 8, 2014].

Baldwin, J.R. & Dixon, J., 2008. *The Canadian Productivity Review Infrastructure Capital : What Is It ? Where Is It ? How Much of It Is There?*

Banerjee, A., Duflo, E. & Qian, N., 2012. On the Road: Access to Transportation Infrastructure and Economic Growth in China. *Transport*, 17897, pp.1–22. Available at: http://www.nber.org/papers/w17897.

Bompard, E., Pons, E. & Wu, D., 2013. Analysis of the structural vulnerability of the interconnected power grid of continental Europe with the Integrated Power System and Unified Power System based on extended topological approach Ettore. *International Transactions on Electrical Energy Systems*, 23(5), pp.620–637. Available at: http://onlinelibrary.wiley.com/doi/10.1002/etep.1618/full [Accessed February 8, 2014].

Brakenridge, R., 2016. Global Active Archive of Large Flood Events. Available at: http://floodobservatory.colorado.edu/Archives/index.html [Accessed December 22, 2016].

Canning, D., 1997. A database of world infrastructure stocks, 1950-95. *World bank policy research working paper*, (1929).

Cao, J., 2010. A Summary of Water Resources Development (我国水利发展综述). *Pearl River Modern Construction*, (2).

Carrera, L. et al., 2015. Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. *Environmental Modelling and Software*, 63, pp.109–122. Available at: http://dx.doi.org/10.1016/j.envsoft.2014.09.016.

Catin, M., Luo, X. & Huffel, C. Van, 2005. *Openness, industrialisation and geographical concentration of activities in China*.

Chan, K.W., 2013. China, Internal Migration. In I. Nees & P. Bellwood, eds. *The*

Encyclopedia of Global Migration. Blackwell Publishing.
Chan, K.W., 2012. Migration and Development Migration and development in China : trends , geography and current issues. *Migration and Development*, 1(December), pp.37–41.
Chen, S., Luo, Z. & Pan, X., 2013. Natural disasters in China: 1900-2011. *Natural Hazards*, 69(3), pp.1597–1605.
China Academy of Transportation Sciences, 2005. *Second National Inland Waterways Census (第二次全国内河航道普查)* Ministry of Transport, ed., China Communications Press.
China Electric Power Yearbook Editorial Committee, 2011. *Total Electricity Consumption in China in 2011 (2011年全社会用电量）*, China Statistics Press.
China Information Centre, 2014. 2012年中国信息化发展综述. Available at: http://www.sic.gov.cn/News/249/2227.htm.
China Southern Power Grid, 2011. The West to East Project. Available at: http://www.ehv.csg.cn/xdds/gk/201309/t20130920_391.html.
China State Council, 2002. *Guidance on the Construction of E-government construction (国家信息化领导小组关于我国电子政务建设指导意见)*, Available at: http://www.neijiang.gov.cn/zwgk/show/20110831102039-475884-00-000.
China State Council, 2006. West-East Gas Project Overview. Available at: http://www.gov.cn/ztzl/2006-01/02/content_145307.htm.
China State Council, 2012. *12th Five-Year Plan for Constructing China's Urban Sewage Treatment and Recycling Facilities ("十二五"全国城镇污水处理及再生利用设施建设规划)*.
China State Council, 2013. *State Council on the Issuance of the" Broadband China" Strategy and the Implementation Plan (国务院关于印发"宽带中国"战略及实施方案的通知)*, Available at: http://www.gov.cn/zwgk/2013-08/17/content_2468348.htm.
Chinese Academy of Sciences, 2015. China Natural Disaster Database (中国自然灾害数据库). Available at: http://www.data.ac.cn/zrzy/G52.asp [Accessed August 10, 2015].
Chinese Census Office of the State Council, 2012. *Tabulation on the 2010 population census of the people's republic of china by county (中国2010人口普查分县资料)*, China Statistics Press.
Chinese Government Network, 2006. Qinghai-Tibet Railway Project. Available at: http://www.audit.gov.cn/n1992130/n1992150/n1992500/2301988.html [Accessed September 22, 2016].
Chinese Ministry of Housing and Urban-Rural Development, 2006. *The Method and Parameters in the Economic Analysis of Construction Projects (Version 3)*,
Christenson, M., Manz, H. & Gyalistras, D., 2006. Climate warming impact on degree-days and building energy demand in Switzerland. *Energy Conversion and Management*, 47(6), pp.671–686.
Civil Aviation Administration of China, 2008. 2020 National Plan for Civil Airports Layout （全国民用机场布局规划）. , pp.1–10. Available at: http://www.caac.gov.cn/I1/I2/200808/P020080819406619590745.pdf [Accessed April 4, 2014].
Civil Aviation Administration of China, 2013. Chinese airport traffic ranking 2012 (2012民航机场业务量排名). *Bulletin of The Chinese Aviation Industry (2012全国机场生产统计公报)*, pp.7–9. Available at: http://www.caac.gov.cn/i1/K3/201303/t20130325_54626.html [Accessed May 1, 2013].
Coelli, F. & Manasse, P., 2014. *The impact of floods on firms' performance*.
Craioveanu, M. & Terrell, D., 2009. *The impact of storms on firm survival: a bayesian spatial econometric model for firm survival*.
Crowther, K.G., Haimes, Y.Y. & Taub, G., 2007. Systemic valuation of strategic preparedness through application of the inoperability input-output model with lessons learned from Hurricane Katrina. *Risk analysis*, 27(5), pp.1345–64. Available at: http://www.ncbi.nlm.nih.gov/pubmed/18076501 [Accessed December 31, 2012].

Culvahouse, T., 2007. *The Tennessee Valley Authority: Design and Persuasion*, New York: Princeton Architectural Press.
Czernich, N. & Falck, O., 2009. Broadband Infrastructure and Economic Growth Broadband Infrastructure and Economic Growth Abstract. *CESifo Working paper Nr. 2861*, 121, pp.505–532.
Dankers, R. & Feyen, L., 2008. Climate change impact on flood hazard in Europe: An assessment based on high-resolution climate simulations. *Journal of Geophysical Research: Atmospheres*, 113(19), pp.1–17.
Davis, C.B. et al., 2014. Enipedia. Available at: http://enipedia.tudelft.nl/maps/PowerPlants.html [Accessed April 28, 2014].
Démurger, S., 2001. Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China? *Journal of Comparative Economics*, 29, pp.95–117. Available at: http://www.sciencedirect.com/science/article/pii/S0147596700916937.
Dinh, T. & Xuan, Y., 2012. On new approaches of assessing network vulnerability: hardness and approximation. *Networking, IEEE/ACM …*, 20(2), pp.609–619. Available at: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6051504 [Accessed February 10, 2014].
Dobbs, R. et al., 2013. *Infrastructure productivity: How to save $1 trillion a year*, Available at: http://www.mckinsey.com/insights/engineering_construction/infrastructure_productivity.
Dueñas-Osorio, L. & Vemuru, S.M., 2009. Cascading failures in complex infrastructure systems. *Structural Safety*, 31(2), pp.157–167. Available at: http://linkinghub.elsevier.com/retrieve/pii/S016747300800057X [Accessed January 20, 2014].
Dutta, D., Herath, S. & Musiake, K., 2003. A mathematical model for flood loss estimation. *Journal of Hydrology*, 277(1–2), pp.24–49. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0022169403000842 [Accessed October 28, 2012].
Editorial Board of China Ports Yearbook, 2012. Port Summary. In *China Ports Yearbook*. China Ports Magazine. Available at: http://tongji.cnki.net/kns55/navi/HomePage.aspx?id=N2012060646&name=YZGAW.
Erath, A. et al., 2009. Vulnerability Assessment of the Swiss Road Network. *Transportation Research Record: Journal of the Transportation Research Board*, 2137(2009 Safety 2009: Security; Emergencies; Management; and School Transportation), pp.118–126. Available at: http://medcontent.metapress.com/index/A65RM03P4874243N.pdf [Accessed February 11, 2014].
ET Geo Wizards, 2013. Allocating demands to service points using ET GeoWizards. Available at: http://www.ian-ko.com/ET_GeoWizards/WhitePapers/gw_allocating_demands_to_services.htm.
Faber, B., 2014. Trade integration, market size, and industrialization: Evidence from China’s national trunk highway system. *Review of Economic Studies*, 81(3), pp.1046–1070.
Fang, W., 2011. *Integrated Risk Governance: Database, risk maps and network platform*, Beijing: Science China Press.
Fay, M. & Yepes, T., 2003. *Investing in Infrastructure: What is Needed from 2000 to 2010?*.
Fomby, T., Ikeda, Y. & Loayza, N. V, 2013. The growth aftermath of natural disasters. *Journal of Applied Econometrics*, 28(October 2011), pp.412–434. Available at: https://www.unisdr.org/we/inform/publications/50177.
Fujita, M., 2010. THE EVOLUTION OF SPATIAL ECONOMICS : FROM THÜNEN TO THE NEW ECONOMIC GEOGRAPHY. *The Japanese Economic Review*, 61(1), pp.1–32.
Geels, F., 2005. Co-evolution of technology and society: The transition in water supply and personal hygiene in the Netherlands (1850-1930) - A case study in multi-level

perspective. *Technology in Society*, 27(3), pp.363–397.
Global Water Partnership, 2015. *China's Water Resources Management Challenge: the "Three Red Lines"*.
Gong, X. et al., 2008. *China's Dilemma: Economic Growth, the Environment and Climate Change* L. Song & W. T. Woo, eds., Available at: http://www.foreignaffairs.com/articles/66773/george-j-gilboy-and-eric-heginbotham/chinas-dilemma?cid=oth-internal-magazine-chinas_dilemma-030111.
Guo, S. et al., 2002. A macro-scale and semi-distributed monthly water balance model to predict climate change impcats in China. *Journal of hydrology*, 268, pp.1–15.
Hall, J.W., Sayers, P.B. & Dawson, R.J., 2005. National-scale Assessment of Current and Future Flood Risk in England and Wales. *Natural Hazards*, 36(1–2), pp.147–164. Available at: http://link.springer.com/10.1007/s11069-004-4546-7.
Hall, J. et al., 2012. *A Fast Track Analysis of strategies for infrastructure provision in Great Britain*, Oxford. Available at: http://www.itrc.org.uk/wordpress/wp-content/FTA/ITRC-FTA-Executive-summary.pdf.
Hall, J.W. et al., 2014. Assessing the Long-Term Performance of Cross-Sectoral Strategies for National Infrastructure. *Journal of Infrastructure Systems*.
Hall, J. et al. eds., 2016. *The Future of National Infrastructure: A System-of-Systems Approach*, Cambridge University Press.
Hall, J.W. et al., 2016. Strategic analysis of the future of national infrastructure. *Proceedings of the Institution of Civil Engineers-Civil Engineering*.
Hallegatte, S., 2008. An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. *Risk Analysis*, 28(3), pp.779–799.
Hallegatte, S., 2013. Modeling the role of inventories in the assessment of natural disaster economic costs : application on hurricane Katrina in Louisiana. *Risk Analysis*, 34(1), pp.152–167.
Hallegatte, S. & Przyluski, V., 2010. *The economics of natural disasters: concepts and methods*.
Haltiwanger, J.C., Lane, J.I. & Spletzer, J.R., 1999. Productivity Differences Across Employers: The Roles of Employer Size, Age, and Human Capital. *American Economic Review*, 89(2), pp.94–98. Available at: http://pubs.aeaweb.org/doi/abs/10.1257/aer.89.2.94.
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(January 2012), pp.256–272. Available at: http://dx.doi.org/10.1016/j.ijdrr.2014.09.005.
Heinsz, W.J., 2002. The Institutional Environment for Infrastructure Investment. *Industrial and Corporate Change*, 11(2), pp.355–389.
Heshmati, A. & Yang, W., 2006. *Contribution of ICT to the Chinese Economic Growth*,
Hines, P., Cotilla-Sanchez, E. & Blumsack, S., 2010. Do topological models provide good information about electricity infrastructure vulnerability? *Chaos (Woodbury, N.Y.)*, 20(3), p.33122. Available at: http://www.ncbi.nlm.nih.gov/pubmed/20887062 [Accessed February 2, 2014].
Hirabayashi, Y. et al., 2013. Global flood risk under climate change. *Nature Publishing Group*, 3(9), pp.816–821. Available at: http://dx.doi.org/10.1038/nclimate1911%5Cnpapers3://publication/doi/10.1038/nclimate1911.
Hochrainer, S., 2009. Assessing the Macroeconomic Impacts of Natural Disasters: Are there any? *World Bank Policy Research Working Paper Series*, (4968), pp.1–41. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1427628.
Holme, P. et al., 2002. Attack vulnerability of complex networks. *Physical review*, 65(5). Available at: http://www.ncbi.nlm.nih.gov/pubmed/12059649.
Hou, Q. & Li, S.-M., 2011. Transport infrastructure development and changing spatial accessibility in the Greater Pearl River Delta, China, 1990–2020. *Journal of Transport Geography*, 19(6), pp.1350–1360. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0966692311001104 [Accessed July 23, 2014].

HSBC, 2011. *Scoring Climate Change Risk*, Hong Kong. Available at: http://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&ved=0CC4QFjAA&url=http%3A%2F%2Fwww.hsbc.com%2F~%2Fmedia%2FHSBC-com%2Fabout-hsbc%2Fin-the-future%2Fpdfs%2F111013-scoring-climate-change-risk.ashx&ei=4lQjU9XGJ-ST0QXH4oHYCA&usg=AFQjCNG_meSvMtf7krtVyYI-A9chLIz20Q&sig2=pFlfNOn0bjG8QjkScKopUA&bvm=bv.62922401,d.d2k.
HSBC, 2012. *No water, no power: is there enough water to fuel China's power expansion?*, Hong Kong. Available at: http://chinawaterrisk.org/notices/china-water-risk-and-hsbc-no-power-no-water-report/.
Hu, X., Hall, J. & Thacker, S., 2014. Too big to fail? The spatial vulnerability of the Chinese infrastructure system to flooding risks. In *The Second International Conference on Vulnerability and Risk Analysis and Management*. Liverpool: American Society of Civil Engineers.
Hu, X. et al., 2015. The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*. Available at: http://link.springer.com/10.1007/s11069-015-2012-3.
IPCC, 2007. *Summary for policymakers*, Available at: http://www.cnv.org/Attach/2008 07 21 item 17 attach 02.pdf [Accessed July 2, 2012].
IPCC, 2012a. Determinants of Risk: Exposure and Vulnerability. In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. pp. 65–108.
IPCC, 2012b. *Managing the risks of extreme events disasters to advance climate change adaptation.*
IPCC, 2014. *IPCC AR5*.
Isaac, M. & van Vuuren, D.P., 2009. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy*, 37(2), pp.507–521.
Jacobson, C.D. & Tarr, J. a, 1995. Ownership and Financing of Infrastructure. Historical Perspectives. *Policy Research Working Paper*, (June), p.38.
Jenkins, K., 2013. Indirect economic costs of drought under future projections of climate change : A case study for Spain. *Natural Hazards*, 69(3), pp.1967–1986.
Johansson, J. & Hassel, H., 2010. An approach for modelling interdependent infrastructures in the context of vulnerability analysis. *Reliability Engineering & System Safety*, 95(12), pp.1335–1344. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0951832010001444 [Accessed January 27, 2014].
Jonkman, S.N. et al., 2008. Integrated hydrodynamic and economic modelling of flood damage in the Netherlands. *Ecological Economics*, 66(1), pp.77–90.
Jongman, B., Ward, P.J. & Aerts, J.C.J.H., 2012. Global exposure to river and coastal flooding: Long term trends and changes. *Global Environmental Change*, 22(4), pp.823–835. Available at: http://dx.doi.org/10.1016/j.gloenvcha.2012.07.004.
Jongman, B. et al., 2014. Increasing stress on disaster-risk finance due to large floods. *Nature Climate Change*, 4(4), pp.1–5.
Kim, H. et al., 2009. Role of rivers in the seasonal variations of terrestrial water storage over global basins. *Geophysical Research Letters*, 36(17), pp.2–6.
Kocornik-mina, A. et al., 2015. *Flooded Cities*, Available at: http://cep.lse.ac.uk/pubs/download/dp1398.pdf.
Koks, E. et al., 2015. Regional disaster impact analysis: comparing Input-Output and Computable General Equilibrium models. *Nat. Hazards Earth Syst. Sci. Discuss.*, 3(11), pp.7053–7088. Available at: http://www.nat-hazards-earth-syst-sci-discuss.net/3/7053/2015/%5Cnhttp://www.nat-hazards-earth-syst-sci-discuss.net/3/7053/2015/nhessd-3-7053-2015.pdf.
Koks, E.E. et al., 2015. Integrated direct and indirect flood risk modeling: Development and sensitivity analysis. *Risk Analysis*, 35(5), pp.882–900.
Kousky, C., 2014. Informing Climate Adaptation: A Review of the Economic Costs of Natural Disasters, Their Determinants, and Risk Reduction Options. *Energy Economics*, 46, pp.576–592.
KPMG, 2008. *Transport in China*, Hong Kong. Available at:

http://www.kpmg.com/CN/en/IssuesAndInsights/ArticlesPublications/Documents/transport-china-0804.pdf.
KPMG, 2009. *Infrastructure in China: Foundation for growth*, Hong Kong. Available at: http://www.kpmg.de/docs/Infrastructure_in_China.pdf.
KPMG, 2012. *China 360 The Renminbi goes global?.*
KPMG, 2013. *Infrastructure in China. Sustaining quality growth*.
Kreibich, H. et al., 2014. Costing natural hazards. *Nature Climate Change*, 4(5), pp.303–306. Available at: http://dx.doi.org/10.1038/nclimate2182.
Kreibich, H. et al., 2007. Flood precaution of companies and their ability to cope with the flood in August 2002 in Saxony, Germany. *Water Resources Research*, 43(3). Available at: http://www.agu.org/pubs/crossref/2007/2005WR004691.shtml [Accessed July 3, 2012].
Kreibich, H. & Bubeck, P., 2013. *Natural Hazards: Direct Costs and Losses Due to the Disruption of Production Processes*, Potsdam. Available at: https://www.unisdr.org/we/inform/publications/50177.
Lardy, R.N. & Fairbank, K.J., 1987. The Chinese economy under stress, 1958–1965. In *The People's Republic, Part 1: The Emergence of Revolutionary China 1949–1965*. Cambridge: Cambridge University Press.
LaRocca, S. et al., 2012. Comparing Topological Performance Measures and Physical Flow Models for Vulnerability Analysis of Power Systems. *Psam11 & Esrel2012*, 35(4), pp.608–623. Available at: http://lup.lub.lu.se/record/2337670.
Lenzen, M. et al., 2013. Building EORA: A Global Multi-Region Input-Output Database at High Country and Sector Resolution. *Economic Systems Research*, 25(1), pp.20–49.
Leontief, W., 1988. *Input-output economics*, Oxford University Press.
Lewis, J.I., 2009. Climate change and security: examining China's challenges in a warming world. *International Affairs*, 85(6), pp.1195–1213. Available at: http://doi.wiley.com/10.1111/j.1468-2346.2009.00857.x.
Li, J. et al., 2013. Modeling imbalanced economic recovery following a natural disaster using input-output analysis. *Risk Analysis*, 33(10), pp.1908–1923.
Li, K. et al., 2012. Flood loss analysis and quantitative risk assessment in China. *Natural Hazards*, 63(2), pp.737–760. Available at: http://www.springerlink.com/index/10.1007/s11069-012-0180-y [Accessed November 5, 2012].
Lim, W.H. et al., Long-term changes in global river flood frequency, socioeconomic benefits of flood defences and residual risk based on CMIP5 climate models.
Lin, E. et al., 2007. China's National Assessment Report on Climate Change (II): Climate change impacts and adaptation. *Advances in Climate Change Research*, 3, pp.6–11.
Liu, B. & Zhang, J., 1999. The Construction of Reservoirs and Flood Control (我国的水库建设与防洪). *China Water Resources*, 7.
Liu, J. & Wu, Y., 2012. Water Sustainability for China and Beyond. *Science*, 337(6095), pp.649–650.
Liu, K., 2014. Current Status and Planning Processes of China's Urban Sewage Treatment System. *People's Daily*. Available at: http://www.people.com.cn/GB/huanbao/56/20030227/932343.html.
Liu, Z., 2006. *Planning and Policy Coordination in China's Infrastructure Development*,
Lockett, H., 2016. China's manufacturing gauge pulled under by heavy flooding. *Financial Times*. Available at: https://www.ft.com/content/4dc1c436-40b2-3107-a4e4-766aaed99914.
Mao, Z. et al., 2009. Vulnerability Analysis of Urban Infrastructures. *2009 International Conference on Industrial and Information Systems*, pp.395–398. Available at: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5116381 [Accessed January 26, 2014].
Marrone, S., Nardone, R. & Tedesco, A., 2013. Vulnerability modeling and analysis for critical infrastructure protection applications. *… Infrastructure Protection*, 6(3–4), pp.217–227. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1874548213000462 [Accessed February 15, 2014].

Matisziw, T.C., Murray, A.T. & Grubesic, T.H., 2009. Exploring the vulnerability of network infrastructure to disruption. *The Annals of Regional Science*, 43(2), pp.307–321. Available at: http://link.springer.com/10.1007/s00168-008-0235-x [Accessed February 12, 2014].
McKinsey, 2009. *Preparing for China's urban billion*.
Mechler, R. et al., 2010. Modelling economic impacts and adaptation to extreme events: Insights from European case studies. *Mitigation and Adaptation Strategies for Global Change*, 15(7), pp.737–762.
Merz, B. et al., 2010. Review article "assessment of economic flood damage." *Natural Hazards and Earth System Science*, 10(8), pp.1697–1724.
Meyer, V. et al., 2013. Review article: Assessing the costs of natural hazards-state of the art and knowledge gaps. *Natural Hazards and Earth System Science*, 13(5), pp.1351–1373.
Ministry of Housing and Urban-Rural Development, 2010. 2006-2010 Communique for the Chinese Urban Drainage and Wastewater Treatment System.
Ministry of Housing and Urban-Rural Development, 2013. Briefing for the 2010 National Plans for Constructing Urban Waste Treatment Facilities (关于2010年9月全国城镇生活垃圾处理设施在建项目进展情况的通报)., pp.1–3. Available at: http://www.mohurd.gov.cn/zcfg/jsbwj_0/jsbwjcsjs/201101/t20110106_201873.html.
Ministry of Housing and Urban-Rural Development, 2014. *Standard for flood control of People's Republic of China (中华人民共和国国家标准防洪标准)*,
Ministry of Industry and Information Technology, 2013. Statistical Bulletin for the National Telecommunications Industry (2012年全国电信业统计公报). Available at: http://www.miit.gov.cn/n11293472/n11293832/n11294132/n12858387/15132905.html.
Ministry of Industry and Information Technology, 2011. *"Twelfth Five Year Plan" for the Digital Information Industry (电子信息制造业"十二五"发展规划)*, Available at: http://www.gov.cn/gzdt/2012-02/24/content_2075829.htm.
Ministry of Rail, 1980. *Classification of Chinese Railway Stations 《铁路车站等级核定办法》*.
Ministry of Rail, 2010. *Chinese Railway Passenger Train Timetable （全国铁路旅客列车时刻表）*, China Railway Publishing House.
Ministry of Rail, 2012. Ministry of Rail: Bulletin of the 2012 Chinese Railway (中华人民共和国铁道部2012年铁道统计公报). , pp.1–5. Available at: http://finance.china.com.cn/roll/20130313/1327154.shtml.
Ministry of Science and Technology of China, 2008. *Chinese Information and Communication Technology (ICT) Development Report (中国信息通信技术发展报告)*,
Ministry of the Environment, 2013. Statistics on national urban sewage treatment facilities in China (全国投运城镇污水处理设施清单). , pp.1–204. Available at: http://www.mep.gov.cn/gkml/hbb/bgg/201305/W020130508476747765965.pdf.
Ministry of Transport, 2009. *A Guide of Chinese Roads《中国路谱》*, Beijing.
Ministry of Transport, 2011. 2010 Bulletin of the Chinese Highway and Waterway Transportation Development (2010年公路水路交通运输行业发展统计公报). , pp.1–19. Available at: http://www.moc.gov.cn/zhuzhan/tongjigongbao/fenxigongbao/hangyegongbao/201104/t20110428_937558.html.
Ministry of Water Resources, 2011a. *Bulletin of Flood and Drought Disasters in China (中国水旱灾害公报）*, Available at: http://www.mwr.gov.cn/zwzc/hygb/zgshzhgb/201212/t20121212_334746.html.
Ministry of Water Resources, 2011b. China Water Resources Bulletin (2011年中国水资源公报 中华人民共和国水利部)., pp.1–22. Available at: http://www.mwr.gov.cn/zwzc/hygb/szygb/qgszygb/201212/t20121217_335297.html.
Ministry of Water Resources, 2012. *Bulletin of Flood and Drought Disasters in China (中国水旱灾害公报）*, Available at:

http://www.mwr.gov.cn/zwzc/hygb/zgshzhgb/201311/t20131104_515863.html.
Ministry of Water Resources, 2014a. *Bulletin of Flood and Drought Disasters in China (中国水旱灾害公报 2014)*.
Ministry of Water Resources, 2014b. *The Bulletin on Flood and Drought Disasters in China 2014 (中国水旱灾害公报2014)*, Available at: http://www.mwr.gov.cn/zwzc/hygb/zgshzhgb/201509/P020150908523746090503.pdf.
Mishra, A.K. & Singh, V.P., 2010. A review of drought concepts. *Journal of Hydrology*, 391(1–2), pp.202–216. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0022169410004257 [Accessed May 24, 2014].
Molinari, D. et al., 2014. Ex post damage assessment: an Italian experience. *Natural Hazards and Earth System Science*, 14(4), pp.901–916. Available at: http://www.nat-hazards-earth-syst-sci.net/14/901/2014/.
Moore, M., 2014. What is China's one-child policy? *The Telegraph*. Available at: http://www.telegraph.co.uk/news/worldnews/asia/china/11197594/What-is-Chinas-one-child-policy.html [Accessed October 12, 2015].
Munnell, A.H., 1992. Policy Watch: Infrastructure Investment and Economic Growth. *Journal of Economic Perspectives*, 6(4), pp.189–198.
Nadiri, M.I. & Mamuneas, T.P., 1994. The effects of public infrastructure and R&D Capital on the cost structure and performance of U.S. Manufacturing Industries. , pp.22–37.
National Bureau of Statistics of China, 2006. Bulletin of the 2005 National Sample Survey on 1% of the population (2005年全国1%人口抽样调查主要数据公报). Available at: http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/qgrkpcgb/200603/t20060316_30326.html [Accessed February 5, 2016].
National Bureau of Statistics of China, 2011. Key Data for the The 2010 Sixth National Census Bulletin (2010年第六次全国人口普查主要数据公报). Available at: http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/qgrkpcgb/201104/t20110428_30327.html [Accessed February 5, 2016].
National Bureau of Statistics of the People's Republic of China, 2016. *Statistical Bulletin on National Economic and Social Development （国民经济和社会发展统计公报）*, Available at: http://www.stats.gov.cn/tjsj/zxfb/201602/t20160229_1323991.html.
National Bureau of Statistics of the People's Republic of China, 2017. National Industry Classification (国民经济行业分类). *Industry Classification*. Available at: http://www.stats.gov.cn/tjsj/tjbz/hyflbz/.
National Development and Reform Commission, 1982. Sixth Five-Year Plan for the People's Republic of China (中华人民共和国国民经济和社会发展第六个五年计划).
National Development and Reform Commission, 1987. Seventh Five-Year Plan for the People's Republic of China (中华人民共和国国民经济和社会发展第七个五年计划).
National Development and Reform Commission, 1996. The Ninth Fivey-Year Plan and Developmental Vision to 2010.
National Development and Reform Commission, 2001a. Tenth Five-Year Plan for the People's Republic of China (中华人民共和国国民经济和社会发展第十个五年计划纲要).
National Development and Reform Commission, 2001b. Western Development Master Plan.
National Development and Reform Commission, 2005. Eleventh Five-Year Plan for the People's Republic of China (中华人民共和国国民经济和社会发展第十一个五年规划纲要). , pp.1–40.
National Development and Reform Commission, 2009. *The 12th National Plan on the Construction of Large and Medium-sized Reservoirs (全国"十二五"大、中型水库建设规划)*.
National Development and Reform Commission, 2011. Twelfth Five-Year Plan for the People's Republic of China (中华人民共和国国民经济和社会发展 第十二个五年规划纲要).

National Energy Administration, 2011. 国家能源科技“十二五”规划 （2011-2015）.
National Energy Administration, 2012. 12th Five-Year Plan for Natural Gas Development (天然气发展“十二五”规划). Available at: http://zfxxgk.nea.gov.cn/auto86/201212/W020121203312244945303.pdf.
National Planning Commission, 2012. *“Twelve Five-Year Plan” for the Digitisation of National Government Services (“十二五”国家政务信息化工程建设规划)*, Available at: http://www.gov.cn/gzdt/2012-05/16/content_2138308.htm.
NOAA, 2015. F18 2012 Nighttime Lights Composite. *Version 4 DMSP-OLS Nighttime Lights Time Series*. Available at: http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html [Accessed July 20, 2015].
OECD, 2008. *Household Behaviour and the Environment: Reviewing the Evidence*,
OECD, 2009. *Urban trends and policy in China*, Available at: http://www.pisa.oecd.org/dataoecd/28/21/42607972.pdf [Accessed December 23, 2012].
Okuyama, Y. & Santos, J.R., 2014. Disaster Impact and Input–Output Analysis. *Economic Systems Research*, 26(1), pp.1–12. Available at: http://www.tandfonline.com/doi/abs/10.1080/09535314.2013.871505.
Oosterhaven, J., 1988. On the Plausibility of the Supply-Driven Input-Output Model. *Journal of Regional Science*, 28(2), pp.203–217. Available at: http://onlinelibrary.wiley.com/doi/10.1111/j.1467-9787.1988.tb01208.x/abstract.
OpenStreetMap Contributors, 2014. OpenStreetMap. Available at: https://www.openstreetmap.org/about [Accessed May 5, 2014].
Oswald, M. & Treat, C., 2013. Assessing Public Transportation Vulnerability to Sea Level Rise: A Case Study Application. *Journal of Public Transportation*, (Fta 2011), pp.59–77. Available at: http://www.nctr.usf.edu/wp-content/uploads/2013/10/16.3_oswald.pdf [Accessed February 8, 2014].
Ouyang, M. et al., 2009. A methodological approach to analyze vulnerability of interdependent infrastructures. *Simulation Modelling Practice and Theory*, 17(5), pp.817–828. Available at: http://dx.doi.org/10.1016/j.simpat.2009.02.001 [Accessed February 13, 2014].
Ouyang, M. et al., 2014. Comparisons of complex network based models and real train flow model to analyze Chinese railway vulnerability. *Reliability Engineering & System Safety*, 123, pp.38–46. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0951832013002792 [Accessed February 13, 2014].
Pant, R. et al., 2016. Critical infrastructure impact assessment due to flood exposure. *Flood Risk Management*, (Special Issue), pp.1–12.
Pappenberger, F. et al., 2012. Deriving global flood hazard maps of fluvial floods through a physical model cascade. *Hydrology and Earth System Sciences*, 16(11), pp.4143–4156.
Peng, X., 2011. China’s demographic history and future challenges. *Science (New York, N.Y.)*, 333(6042), pp.581–587.
Penning-Rowsell et al., 2003. *The Benefits of Flood and Coastal Defence: Techniques and Data for 2003*, London: Middlesex University.
Pérez, L.P. y & Barreiro-Hurlé, J., 2009. Assessing the socio-economic impacts of drought in the Ebro River Basin. *Spanish Journal of Agricultural …*, 7(2), pp.269–280. Available at: http://revistas.inia.es/index.php/sjar/article/viewArticle/418 [Accessed July 23, 2013].
Poljanšek, K. et al., 2017. *Science for disaster risk management 2017: knowing better and losing less*, Luxembourg. Available at: http://www.preventionweb.net/publications/view/53319.
PONCET, S., 2003. Measuring Chinese domestic and international integration. *China Economic Review*, 14(1), pp.1–21. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1043951X02000834.
Raschky, P. a., 2008. Institutions and the losses from natural disasters. *Natural Hazards and Earth System Science*, 8, pp.627–634.

Redding, S.J., 2010. The empirics of new economic geography. *Journal of Regional Science*, 50(1), pp.297–311.
Regmi, M.B. & Hanaoka, S., 2011. A survey on impacts of climate change on road transport infrastructure and adaptation strategies in Asia. *Environmental Economics and Policy Studies*, 13(1), pp.21–41. Available at: http://www.springerlink.com/index/10.1007/s10018-010-0002-y [Accessed November 26, 2012].
Revi, A. et al., 2014. *ChapteClimate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*,
Rimmer, P.J., 1997. China's Infrastructure and Economic Development in the 21st Century. *Futures*, 29(435–465).
Rose, A., 2004. Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation. In Y. Okuyama & S. Chang, eds. *Modeling spatial and economic impacts of disasters*. Springer Berlin / Heidelberg, pp. 13–36.
Rose, A. & Liao, S.Y., 2005. Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of Regional Science*, 45(1), pp.75–112. Available at: http://www.scopus.com/inward/record.url?eid=2-s2.0-14744293206&partnerID=tZOtx3y1.
Rose, A. & Wei, D., 2013. Estimating the Economic Consequences of a Port Shutdown: the Special Role of Resilience. *Economic Systems Research*, 25(2), pp.212–232. Available at: http://www.tandfonline.com/doi/abs/10.1080/09535314.2012.731379.
Sahoo, P., Dash, R.K. & Nataraj, G., 2010. *Infrastructure Development and Economic Growth in China*,
Schaller, N. et al., 2016. Human influence on climate in the 2014 Southern England winter floods and their impacts. *Nature Climate Change*, 6, pp.627–634.
Schumacher, I. & Strobl, E., 2011. Economic development and losses due to natural disasters: The role of hazard exposure. *Ecological Economics*, 72, pp.97–105. Available at: http://dx.doi.org/10.1016/j.ecolecon.2011.09.002.
Shaw, S.-L. et al., 2009. China's airline consolidation and its effects on domestic airline networks and competition. *Journal of Transport Geography*, 17(4), pp.293–305. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0966692309000192 [Accessed December 22, 2014].
De Sherbinin, A., Schiller, A. & Pulsipher, A., 2007. The vulnerability of global cities to climate hazards. *Environment and Urbanization*, 19(1), pp.39–64. Available at: http://eau.sagepub.com/cgi/doi/10.1177/0956247807076725 [Accessed November 17, 2012].
Shi, P. ed., 2011. *Atlas of Natural Disaster Risk in China （中国自然灾害风险地图集）*, Beijing: Science China Press.
Shuang, Q., Zhang, M. & Yuan, Y., 2014. Node vulnerability of water distribution networks under cascading failures. *Reliability Engineering & System Safety*, 124, pp.132–141. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0951832013003153 [Accessed February 14, 2014].
Song, S. & Zhang, K.H., 2002. Urbanisation and City Size Distribution in China. *Urban Studies*, 39(12), pp.2317–2327.
Song, Y., 2017. Against the "No. 1 flood in 2017 in the Yangtze River Basin." *Xinhua News*. Available at: http://www.gov.cn/xinwen/2017-07/03/content_5207453.htm [Accessed July 6, 2017].
South-to-North Water Diversion Committee, 2006. Introduction to the South-to-North Water Diversion Project. Available at: http://www.nsbd.gov.cn/zx/gczs/200603/t20060302_188126.html [Accessed September 22, 2016].
Stanway, D., 2011. China power crunch to worsen as drought slashes hydro. *Reuters*. Available at: http://www.reuters.com/article/2011/05/25/us-china-drought-hydropower-idUSTRE74O1BK20110525 [Accessed August 26, 2015].
State Grid Energy Research Institute, 2014. Large-scale Ultra High Voltage Transmission is

in rapid development in China (特高压跨区输电应更大规模地快速发展). *China National Grid Highlight Report*. Available at: http://www.sgeri.sgcc.com.cn/html/sgeri/col1080000035/2014-11/14/20141114105657125741045_1.html [Accessed July 15, 2015].
Steenge, A.E. & Bockarjova, M., 2007. Thinking about imbalances in post-catastrophe economies: An input - output based proposition. *Economic Systems Research*, 19(2), pp.205–223. Available at: http://content.ebscohost.com/pdf19_22/pdf/2007/EYS/01Jun07/25192161.pdf?T=P&P=AN&K=25192161&S=R&D=bth&EbscoContent=dGJyMMvl7ESeqK44v+vlOLCmr0qeprNSsKm4SbeWxWXS&ContentCustomer=dGJyMPGptk23p7NRuePfgeyx44Dt6fIA%5Cnhttp://www.scopus.com/record/display.url?eid=.
Stock, J. & Watson, M., 2003. *Introduction to Econometrics* 1st ed., Pearson.
Stocker, T.. et al., 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, United Kingdom.
Straub, S., 2008. Infrastructure and Growth in Developing Countries : Recent Advances and Research Challenges. *World Bank POLICY RESEARCH WORKING PAPER*, (January), p.54. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1080475.
Swanson, A., 2015. How China used more cement in 3 years than the U.S. did in the entire 20th Century. *Washington Post*. Available at: https://www.washingtonpost.com/news/wonk/wp/2015/03/24/how-china-used-more-cement-in-3-years-than-the-u-s-did-in-the-entire-20th-century/?utm_term=.2e6ff1670fe3 [Accessed July 6, 2017].
Swyngedouw, E., Moulaert, F. & Arantxa, R., 2002. New Geographies of Power , Exclusion and Injustice Neoliberal Urbanization in Europe : Large-Scale Urban Development Projects and the New Urban Policy. *Antipode*, 34, pp.542–577.
Takata, K., Emori, S. & Watanabe, T., 2003. Development of the minimal advanced treatments of surface interaction and runoff. *Global and Planetary Change*, 38(1–2), pp.209–222.
Tang, H.S. et al., 2013. Vulnerability of population and transportation infrastructure at the east bank of Delaware Bay due to coastal flooding in sea-level rise conditions. *Natural Hazards*, 69(1), pp.141–163. Available at: http://link.springer.com/10.1007/s11069-013-0691-1 [Accessed February 14, 2014].
Thacker, S., Barr, S., et al., 2017. Geographic Hotspots of Critical National Infrastructure. *Risk Analysis*.
Thacker, S., Pant, R. & Hall, J.W., 2017. System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *Reliability Engineering and System Safety*, 167(April), pp.30–41. Available at: http://dx.doi.org/10.1016/j.ress.2017.04.023.
The Climate Group, 2015. *China analysis 2015*, Available at: https://www.theclimategroup.org/sites/default/files/archive/files/RE100-China-analysis.pdf.
The Harvard WorldMap Project, 2014. Harvard ChinaMap. Available at: http://worldmap.harvard.edu/chinamap/ [Accessed April 28, 2015].
The United Nations Office for Disaster Risk Reduction, 2017. China Disaster & Risk Profile. *PreventionWeb*. Available at: http://www.preventionweb.net/countries/chn/data/ [Accessed January 23, 2017].
Tierney, K.J. & Nigg, J.M., 1995. *Business Vulnerability to Disaster-Related Lifeline Disruption*.
Torrisi, G., 2009. *Public Infrastructure: Definition, Classification and Measurement Issues*, Available at: http://mpra.ub.uni-muenchen.de/12990/.
Tukker, A. et al., 2008. Towards a global multi-regional environmentally extended input – output database. *Ecological Economics*, 68(7), pp.1928–1937. Available at: http://dx.doi.org/10.1016/j.ecolecon.2008.11.010.
Uddin, N. et al., 2015. Sustainable development outcomes of coal mine methane clean development mechanism Projects in China. *Renewable and Sustainable Energy*

Reviews, 45, pp.1–9. Available at: http://dx.doi.org/10.1016/j.rser.2015.01.053.
UK HM Government, 2013. *Green Book supplementary guidance: discounting*.
UNISDR, 2011. *Towards a post-2015 framework for disaster risk reduction*, Available at: http://www.unisdr.org/we/inform/publications/25129.
Van Der Veen, A. & Logtmeijer, C., 2005. Economic hotspots: Visualizing vulnerability to flooding. *Natural Hazards*, 36(1–2), pp.65–80.
Vu, T.B. & Noy, I., 2013. *Natural disasters and firms in Vietnam Tam Bang Vu and Ilan Noy*, Available at: http://researcharchive.vuw.ac.nz/xmlui/handle/10063/3063.
Wang, J. et al., 2009. Spatiotemporal evolution of China's railway network in the 20th century: An accessibility approach. *Transportation Research Part A: Policy and Practice*, 43(8), pp.765–778. Available at: http://linkinghub.elsevier.com/retrieve/pii/S096585640900072X [Accessed December 31, 2014].
Wang, J., Mo, H. & Wang, F., 2014. Evolution of air transport network of China 1930–2012. *Journal of Transport Geography*. Available at: http://linkinghub.elsevier.com/retrieve/pii/S096669231400026X [Accessed August 4, 2014].
Wang, S. et al., 2013. Vulnerability analysis of interdependent infrastructure systems under edge attack strategies. *Safety Science*, 51(1), pp.328–337. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0925753512002007 [Accessed February 14, 2014].
Wang, S., Hong, L. & Chen, X., 2012. Vulnerability analysis of interdependent infrastructure systems: A methodological framework. *Physica A: Statistical Mechanics and its Applications*, 391(11), pp.3323–3335. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0378437111009794 [Accessed August 5, 2014].
Wang, Y. & Yan, Y., 2009. Quantitative assessment of the target completion rate for 10 Chinese five-year plans (中国10个五年计划完成情况的定量评估). *Contemporary China History Studies*, 16(5).
Ward, P.J. et al., 2013. Assessing flood risk at the global scale: model setup, results, and sensitivity. *Environmental Research Letters*, 8(4), p.44019. Available at: http://stacks.iop.org/1748-9326/8/i=4/a=044019?key=crossref.2ecb02eb38c1de207a81abed549fe415 [Accessed May 22, 2014].
Ward, P.J. et al., 2017. A global framework for future costs and benefits of river-flood protection in urban areas. *Nature Climate Change*, (July), pp.1–7.
Wilhelmi, O. V & Wilhite, D.A., 2002. Assessing Vulnerability to Agricultural Drought : A Nebraska Case Study. *Drought Mitigation Center Faculty Publications*.
Wooldridge, J., 2003. *Introductory Econometrics: A Modern Approach*, South-Western Educational Publishing.
World Bank, 2004. *Understanding the Economic and Financial Impacts of Natural Disasters*, Washington, DC. Available at: http://elibrary.worldbank.org/doi/book/10.1596/0-8213-5685-2?queryID=987%2F1899984.
World Bank, 2005. *Waste Management in China : Issues and Recommendations May 2005*.
World Bank, 2007. *An Overview of China's Transport Sector - 2007*.
World Bank, 2014. Bringing China's Energy Efficiency Experience to the World: Knowledge Exchange with Asian Countries. Available at: http://www.worldbank.org/en/news/feature/2014/06/27/bringing-chinas-energy-efficiency-experience-to-the-world-knowledge-exchange-with-asian-countries [Accessed February 3, 2016].
World Bank, 2015a. World Development Indicators - GDP Growth Rate. *Google Public Data Explorer*. Available at: https://www.google.co.uk/publicdata/explore?ds=d5bncppjof8f9_&met_y=ny_gdp_mktp_kd_zg&idim=country:CHN:IND:USA&hl=en&dl=en [Accessed October 12, 2015].

World Bank, 2015b. World Development Indicators - GDP Per Capita. *Google Public Data Explorer*. Available at: https://www.google.co.uk/publicdata/explore?ds=d5bncppjof8f9_&met_y=ny_gdp_pcap_cd&idim=country:CHN:IND&hl=en&dl=en [Accessed October 12, 2015].
World Bank, 2015c. World Development Indicators - Population. *Google Public Data Explorer*. Available at: https://www.google.co.uk/publicdata/explore?ds=d5bncppjof8f9_&met_y=sp_pop_totl&idim=country:CHN:IND&hl=en&dl=en [Accessed October 11, 2015].
World Bank, 2015d. World Development Indicators - Population Growth Rate. *Google Public Data Explorer*. Available at: https://www.google.co.uk/publicdata/explore?ds=d5bncppjof8f9_&met_y=sp_pop_grow&idim=country:CHN:IND:USA&hl=en&dl=en [Accessed October 12, 2015].
Wu, S., Pan, T. & He, S., 2012. Climate Change Risk Research : A Case Study on Flood Disaster Risk in China. , 3(2), pp.92–98.
Wu, W., 1999. Reforming China's Institutional Environment for Urban Infrastructure Provision. *Urban Studies*, 36(13), pp.2263–2282. Available at: http://usj.sagepub.com/cgi/doi/10.1080/0042098992412 [Accessed September 11, 2014].
Xie, J. et al., 2013. Board-scale reliability of the flood defence infrastructure within the Taihu Basin , China. *Journal of Flood Risk Management*, 6(1), pp.42–56.
Xinhua News, 2016. China's Thirteenth Five-Year Plan （中华人民共和国国民经济和社会发展第十三个五年规划纲要）. Available at: http://news.xinhuanet.com/politics/2016lh/2016-03/17/c_1118366322.htm [Accessed October 31, 2016].
Yamamura, E., 2013. Impact of natural disasters on income inequality: Analysis using panel data during the period 1965 to 2004. *International Economic Journal*, 29(3).
Yamano, N. & Ahmad, N., 2006. *The OECD Input-Output Database: 2006 Edition*, Paris. Available at: http://www.oecd.org/science/sci-tech/37585924.pdf.
Yamano, N., Kajitani, Y. & Shumuta, Y., 2007. Modeling the Regional Economic Loss of Natural Disasters: The Search for Economic Hotspots. *Economic Systems Research*, 19(2), pp.163–181.
Yamazaki, D. et al., 2011. A physically based description of floodplain inundation dynamics in a global river routing model. *Water Resources Research*, 47(4), pp.1–21.
Yamazaki, D. et al., 2014. Water Resources Research. *Water Resources Research*, 50, pp.3467–3480.
Yang, X., Keat Tok, S. & Su, F., 2008. The privatization and commercialization of China's airports. *Journal of Air Transport Management*, 14(5), pp.243–251. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0969699708000574 [Accessed December 14, 2014].
Yin, N., 2010. Chinese high-speed rail can breakeven (中国高铁实现盈亏平衡没有悬念). *Xinhua News*. Available at: http://jjckb.xinhuanet.com/cjxw/2010-08/12/content_248195.htm [Accessed July 11, 2015].
Yu, N. et al., 2012. Transport Infrastructure, Spatial Clusters and Regional Economic Growth in China. *Transport Reviews*, 32(1), pp.3–28. Available at: http://www.tandfonline.com/doi/abs/10.1080/01441647.2011.603104 [Accessed August 8, 2014].
Zarafshani, K. et al., 2012. Drought vulnerability assessment: The case of wheat farmers in Western Iran. *Global and Planetary Change*, 98–99, pp.122–130. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0921818112001762 [Accessed November 29, 2012].
Zhang, L., 2017. Sluggish hydropower perfomrance: coal consumption grows at six major coastal power plants. *Energy Information and Consulting Service Provider*. Available at: http://www.china5e.com/news/news-994310-1.html [Accessed September 28, 2017].
Zhang, X., 2009. Development of China's Electricity Sector - Last 60 Years (中国电力发展60年60事). *China Power Enterprise Management (中国电力企业管理)*.

Appendix 1. Route type and carrying capacity

Category	Carrying Capacity (Persons)
Electric Multiple Unit (EMU)	915
Ordinary Express	1000
Temporary Trains	1888
Intercity High Speed Rail	560
Fast trains	1062*
Direct Express	1062*
Fast Express with Air Conditioning	538
Ordinary Express with Air Conditioning	1254
Express with Air Conditioning	1288
High Speed Electric Multiple Unit	1053

*Data on fast and direct express trains are not available; therefore we calculate the average carrying capacity based on the other types of trains.

Appendix 2. List of cities exposed to high flooding risks for all infrastructure sub-sectors (rail, aviation, shipping, electricity and wastewater).

City	*Province*
Chaohu	Anhui
Chuzhou	Anhui
Hefei	Anhui
Ma'anshan	Anhui
Suzhou	Anhui
Wuhu	Anhui
Xuancheng	Anhui
Beijing	Beijing
Dongguan	Guangdong
Foshan	Guangdong
Guangzhou	Guangdong
Huizhou	Guangdong
Jiangmen	Guangdong
Qingyuan	Guangdong
Zhaoqing	Guangdong
Zhongshan	Guangdong
Zhuhai	Guangdong
Baoding	Hebei
Cangzhou	Hebei
Handan	Hebei
Hengshui	Hebei
Langfang	Hebei
Shijiazhuang	Hebei
Tangshan	Hebei
Xingtai	Hebei
Anyang	Henan
Hebi	Henan
Jiaozuo	Henan
Kaifeng	Henan
Luohe	Henan
Puyang	Henan
Xinxiang	Henan
Xuchang	Henan
Zhengzhou	Henan
Zhoukou	Henan
Changzhou	Jiangsu
Nanjing	Jiangsu
Nantong	Jiangsu
Suzhou	Jiangsu
Taizhou	Jiangsu
Wuxi	Jiangsu
Xuzhou	Jiangsu
Yancheng	Jiangsu

Yangzhou	Jiangsu
Zhenjiang	Jiangsu
Anshan	Liaoning
Fuxin	Liaoning
Jinzhou	Liaoning
Liaoyang	Liaoning
Panjin	Liaoning
Shenyang	Liaoning
Binzhou	Shandong
Dezhou	Shandong
Heze	Shandong
Jinan	Shandong
Jining	Shandong
Liaocheng	Shandong
Linyi	Shandong
Tai'an	Shandong
Zaozhuang	Shandong
Zibo	Shandong
Shanghai	Shanghai
Tianjin	Tianjin
Hangzhou	Zhejiang
Huzhou	Zhejiang
Jiaxing	Zhejiang
Ningbo	Zhejiang
Shaoxing	Zhejiang

Appendix 3. List of cities exposed to high drought risks for the electricity sub-sector.

City	*Province*
Weinan	Shaanxi
Bengbu	Anhui
Bozhou	Anhui
Chaohu	Anhui
Chuzhou	Anhui
Fuyang	Anhui
Hefei	Anhui
Huaibei	Anhui
Huainan	Anhui
Lu'an	Anhui
Ma'anshan	Anhui
Suzhou	Anhui
Wuhu	Anhui
Xuancheng	Anhui
Beijing	Beijing
Dongguan	Guangdong
Huizhou	Guangdong
Jiangmen	Guangdong
Yangjiang	Guangdong
Bijie	Guizhou
Zunyi	Guizhou
Chengde	Hebei
Handan	Hebei
Langfang	Hebei
Qinhuangdao	Hebei
Shijiazhuang	Hebei
Tangshan	Hebei
Xingtai	Hebei
Zhangjiakou	Hebei
Qiqihar	Heilongjiang
Qitaihe	Heilongjiang
Shuangyashan	Heilongjiang
Anyang	Henan
Hebi	Henan
Jiaozuo	Henan
Jiyuan shi	Henan
Kaifeng	Henan
Luohe	Henan
Luoyang	Henan
Nanyang	Henan
Pingdingshan	Henan
Puyang	Henan
Sanmenxia	Henan

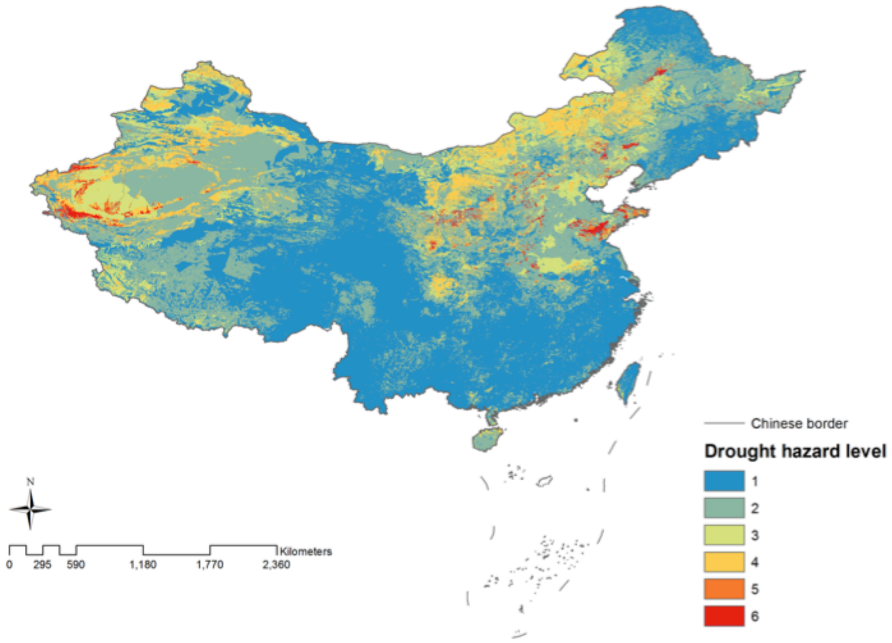
Xinxiang	Henan
Xinyang	Henan
Xuchang	Henan
Zhengzhou	Henan
Zhoukou	Henan
Zhumadian	Henan
Jingmen	Hubei
Suizhou Shi	Hubei
Xiangfan	Hubei
Yichang	Hubei
Changde	Hunan
Zhangjiajie	Hunan
Changzhou	Jiangsu
Huai'an	Jiangsu
Nanjing	Jiangsu
Wuxi	Jiangsu
Yangzhou	Jiangsu
Zhenjiang	Jiangsu
Benxi	Liaoning
Fushun	Liaoning
Huludao	Liaoning
Liaoyang	Liaoning
Shenyang	Liaoning
Hohhot	Nei Mongol
Hulunbuir	Nei Mongol
Ordos	Nei Mongol
Ulaan Chab	Nei Mongol
Yan'an	Shaanxi
Yulin	Shaanxi
Dezhou	Shandong
Heze	Shandong
Jinan	Shandong
Jining	Shandong
Laiwu	Shandong
Liaocheng	Shandong
Linyi	Shandong
Qingdao	Shandong
Rizhao	Shandong
Tai'an	Shandong
Weifang	Shandong
Yantai	Shandong
Zaozhuang	Shandong
Zibo	Shandong
Changzhi	Shanxi
Datong	Shanxi

Jincheng	Shanxi
Jinzhong	Shanxi
Linfen	Shanxi
Luliang	Shanxi
Shuozhou	Shanxi
Taiyuan	Shanxi
Xinzhou	Shanxi
Yangquan	Shanxi
Yuncheng	Shanxi
Tianjin	Tianjin

Appendix 4. List of cities that are exceptionally vulnerable in terms of infrastructure alone.

City	*Province*
Xuancheng	Anhui
Beijing	Beijing
Baoding	Hebei
Langfang	Hebei
Tangshan	Hebei
Changzhou	Jiangsu
Nantong	Jiangsu
Suzhou	Jiangsu
Taizhou	Jiangsu
Wuxi	Jiangsu
Zhenjiang	Jiangsu
Shanghai	Shanghai
Tianjin	Tianjin
Hangzhou	Zhejiang
Huzhou	Zhejiang
Jiaxing	Zhejiang
Ningbo	Zhejiang
Shaoxing	Zhejiang

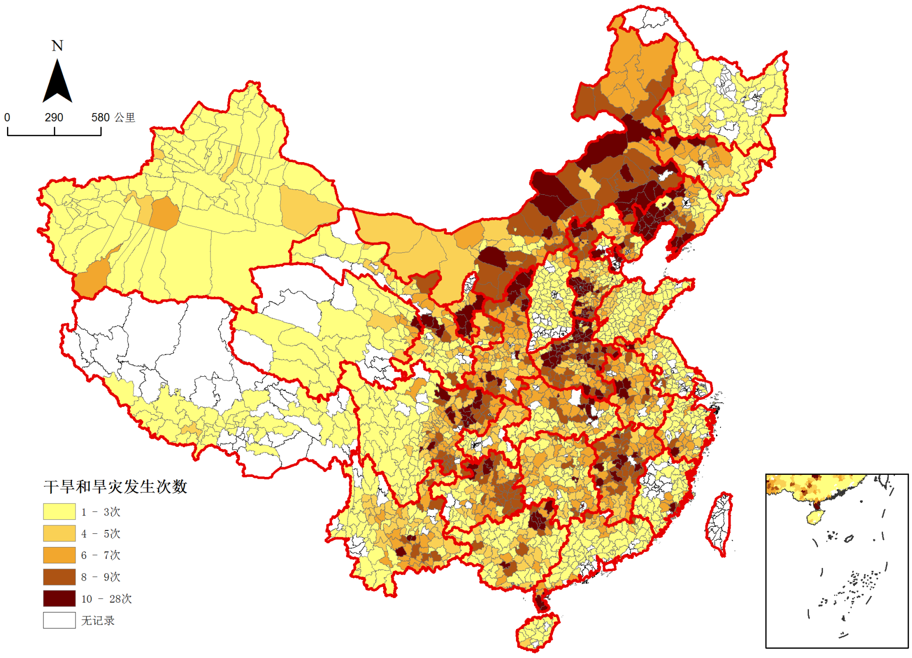
Here we summarise the verification process as in the Atlas of Natural Disaster Risk in China (Shi, 2011). Appendix 5 shows the drought hazard map from the Atlas. The red areas demonstrate higher potential for experiencing drought events.



Appendix 5. Drought hazard map

To verify the results, data were obtained from the "China Natural Disaster Database" which contains a record of natural disasters at county level, reported in Chinese provincial newspapers between 1949 and 2010 (Chinese Academy of Sciences 2015). The database includes information on the start and end times, location, disaster type, impact and journal sources.

Appendix 6 below shows the historical records of drought events between 1949-2010 at county level. Darker red areas demonstrate higher incidents of flooding events. Blank cells contain no data. As can be seen from the figure below, between 1949--2010, drought events occurred mainly in northern China.



Appendix 6. Drought frequency at county level, for example, the maroon counties have an aggregate drought frequency in the range of 10-28 between 1949 and 2010.

As counties contain multiple values of hazard level (Appendix 6), the average hazard level was calculated for each county. The correlation between the average hazard level for that county was then plotted with the historical hazard frequency for that county. Pearson and Spearman correlation tests were conducted and it was demonstrated that the correlation between the hazard level map (Appendix 5) and the historical map (Appendix 6) is significant at 1%. Results of the statistical tests are reported in the table below (Appendix 7). For more verification details, please refer to the Atlas of Natural Disasters in China (Shi, 2011).

Appendix 7. Correlation between drought hazard map and historical drought map at county level.

Test	Average hazard level per county	
	Coefficient	Significance
Pearson	0.176	0.000**
Spearman	0.165	0.000**

Notes: No. of observations 2118； ** at 1% significance level.

Appendix 8. IO accounts of the Chinese economy

Sector number	Sector name	Chinese
1	Agriculture, forestry, animal husbandry and fishery industry	农林牧渔业
2	Coal mining and processing industry	煤炭开采和洗选业
3	Oil and gas exploration industry	石油和天然气开采业
4	Metal mining industry	金属矿采选业
5	Other non-metallic mineral mining industry	非金属矿及其他矿采选业
6	Food manufacturing and tobacco processing industry	食品制造及烟草加工业
7	Textile industry	纺织业
8	Textile, leather and feather products industry	纺织服装鞋帽皮革羽绒及其制品业
9	Wood processing and furniture manufacturing	木材加工及家具制造业
10	Paper printing, educational and sports goods manufacturing	造纸印刷及文教体育用品制造业
11	Petroleum processing, coking and nuclear fuel processing industry	石油加工、炼焦及核燃料加工业
12	Chemical industry	化学工业
13	Non-metallic mineral products industry	非金属矿物制品业
14	Metal smelting and rolling processing industry	金属冶炼及压延加工业
15	Fabricated metal products industry	金属制品业
16	General, special equipment manufacturing industry	通用、专用设备制造业
17	Transportation equipment manufacturing	交通运输设备制造业
18	Electrical machinery and equipment manufacturing industry	电气机械及器材制造业
19	Communications equipment, computers and other electronic equipment manufacturing	通信设备、计算机及其他电子设备制造业
20	Instruments and office machinery manufacturing	仪器仪表及文化办公用机械制造业
21	Crafts and other manufacturing industries (including scrap waste)	工艺品及其他制造业(含废品废料)
22	Electricity, heat production and supply industry	电力、热力的生产和供应业
23	Gas production and supply	燃气生产和供应业
24	Water production and supply industry	水的生产和供应业
25	Building industry	建筑业
26	Transportation and warehousing	交通运输及仓储业
27	Postal services	邮政业
28	Information transmission, computer services and software industry	信息传输、计算机服务和软件业
29	Wholesale and retail trade	批发和零售业

30	Accommodation and catering industry	住宿和餐饮业
31	Financial industry	金融业
32	Real estate	房地产业
33	Leasing and business services	租赁和商务服务业
34	Research and development industry	研究与试验发展业
35	Integrated technology services	综合技术服务业
36	Water conservancy, environment and public facilities management industry	水利、环境和公共设施管理业
37	Residential services and other services	居民服务和其他服务业
38	Education	教育
39	Health, social security and social welfare	卫生、社会保障和社会福利业
40	Culture, sports and entertainment	文化、体育和娱乐业
41	Public administration and social organisations	公共管理和社会组织

Appendix 9. Statements of Authorship

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the articles below, which are part of her DPhil dissertation:

- Hu, X., Hall, J.W. and Thacker, S. (2014) Too big to fail? the spatial vulnerability of the Chinese infrastructure system to flooding risks, in: Second International Conference on Vulnerability and Risk Analysis and Management (ICVRAM) and the Sixth International Symposium on Uncertainty, Modeling, and Analysis (ISUMA). *Vulnerability, Uncertainty and Risk*: 704-714.
- Hu, X., Hall, J.W., Shi, P. and Lim, W-H. (2015) The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*, 80(2): 1083-1118.
- Hu, X., Pant, R., Hall, J., Surminski. S (2017) Multi-scale assessment of the economic impacts of flooding on the Chinese manufacturing sector: firm to macro level analysis. Submitted to Risk Analysis.
- Hu, X., Pant, R., Lim, W., Lu, X., Hall, J. (2017) Variability of flood exposure in China's infrastructure systems in the context of a changing climate. Submitted to Nature Climate Change.
- Hu, X., Hall, J.W. (2017) China's Infrastructure (R)evolution: Exploring the Drivers of Infrastructure Development. Submitted to International Journal of Urban and Regional Research.

Name: Professor Jim Hall

Address: Environmental Change Institute, South Parks Road, OX1 3QY

Signature: JW Hall

Date: 5/10/17

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the articles below, which are part of her DPhil dissertation:

- Hu, X., Pant, R., Hall, J., Surminski. S (2017) Multi-scale assessment of the economic impacts of flooding on the Chinese manufacturing sector: firm to macro level analysis. Submitted to Risk Analysis.
- Hu, X., Pant, R., Lim, W., Lu, X., Hall, J. (2017) Variability of flood exposure in China's infrastructure systems in the context of a changing climate. Submitted to Nature Climate Change.

Name: Dr Raghav Pant

Address: Environmental Change Institute, South Parks Road, OX1 3QY

Signature:

Raghav Pant

Date: 1st October 2017

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the articles below, which are part of her DPhil dissertation:

- Hu, X., Hall, J.W., Shi, P. and Lim, W-H. (2015) The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*, 80(2): 1083-1118.
- Hu, X., Pant, R., Lim, W., Lu, X., Hall, J. (2017) Variability of flood exposure in China's infrastructure systems in the context of a changing climate. Submitted to Nature Climate Change.

Name: Dr Wee Ho Lim

Address: Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences

Signature:

Date: 4th October 2017

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the article below, which is part of her DPhil dissertation:

- Hu, X., Hall, J.W. and Thacker, S. (2014) Too big to fail? the spatial vulnerability of the Chinese infrastructure system to flooding risks, in: Second International Conference on Vulnerability and Risk Analysis and Management (ICVRAM) and the Sixth International Symposium on Uncertainty, Modeling, and Analysis (ISUMA). *Vulnerability, Uncertainty and Risk*: 704-714.

Name: Dr Scott Thacker

Address: Environmental Change Institute, South Parks Road, OX1 3QY

Signature:

Date: 01/10/2017

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the article below, which is part of her DPhil dissertation:

- Hu, X., Pant, R., Hall, J., Surminski. S (2017) Multi-scale assessment of the economic impacts of flooding on the Chinese manufacturing sector: firm to macro level analysis. Submitted to Risk Analysis.

Name: Dr Swenja Surminksi

Address: Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science (LSE)

Signature:

Date:
2nd October 2017

Certificate of Authorship of Dissertation Work for Xi Hu

To Whom It May Concern

I hereby certify that Xi Hu carried out the majority of the work contained in the article below, which is part of her DPhil dissertation:

- Hu, X., Pant, R., Lim, W., Lu, X., Hall, J. (2017) Variability of flood exposure in China's infrastructure systems in the context of a changing climate. Submitted to Nature Climate Change.

Name: Professor Lu Xi

Address: School of Environment, Tsinghua University

Signature:

Xi Lu

Date: 2017/10/02