

The spatial exposure of China's infrastructure system to flooding risks in the context of climate change

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Abstract

Extreme weather events in China, expected to become increasingly common because of climate change, pose a grave threat to essential infrastructure that provides running water, electricity, road and railway connections. This research looks at the fundamental issues of understanding the vulnerability and risks to Chinese infrastructures due to adverse climate impacts. We have developed a suite of infrastructure (energy, transport, water, waste and ICT) models to understand how exposed China's infrastructure is to various potential climate change impacts. We use a concept called the “infrastructure criticality hotspot” which is defined as a geographical location where there is a concentration of critical infrastructure, measured according to the number of customers directly or indirectly dependent upon it. Key findings from our research show that China's top infrastructure vulnerability hotspots are Beijing, Tianjin, Jiangsu, Shanghai and Zhejiang. Using spatial hydrological models, we then investigate how these areas may be affected by flooding. Our research shows that railways, aviation, shipping, electricity, and wastewater in Anhui, Beijing, Guangdong, Hebei, Henan, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang — and their 66 cities — are exceptionally exposed. The average number of people who use these services and could be disrupted by the impacts of flooding stands at 103 million.

To deepen the understanding of how climate change will affect the Chinese infrastructure system, we look at how future flooding probabilities will change according to different emission scenarios. To this end, we use the results of a global river routing model – the Catchment-Based Macro-scale Floodplain (CaMa-Flood) – to project future flood hazard given scenarios RCP 4.5 and RC 8.5. We observe that most models show that infrastructure hotspots are in areas of increasing flooding probabilities. Jiangsu, Anhui, Hubei, northern Hunan and Jiangxi, western Heilongjiang, eastern Inner Mongolia, Liaoning provinces all may incur increasing flood hazard for their infrastructures. To demonstrate infrastructure exposure to changing flood risks more specifically, we show a case study of the electricity sector and its exposure to changing flood probabilities given RCP 4.5 and RCP 8.5 for a set of optimistic, medium and pessimistic scenarios.

1. Introduction

China used more concrete in 3 years (2011 – 2013) than the U.S. used in the entire 20th century, much of which was for building infrastructure (Swanson 2015). Between 2011 and 2015, investment in fixed assets including transport, energy and digital communication grew from 31 trillion RMB to 56 trillion RMB (National Bureau of Statistics of the People’s Republic of China 2016). 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. Flooding in 2014 in China was 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 the same event 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 2014; Ministry of Water Resources 2011). This year (2017), China is experiencing an 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).

Our paper aims to understand how the Chinese infrastructure system will be exposed to varying flooding hazard in a changing climate. First, we examine current exposure of infrastructure assets and networks in China to flood hazard. Second, we apply a global river routing (CaMa-Flood) model to the network-based infrastructure database and explore how Chinese infrastructure assets will face changing flood probabilities between 2016 and 2055, using the electricity sector as a case study. Section 2 discusses how we conduct our current exposure analysis. Section 3 presents our methodology for estimating future exposure. Section 4 describes our results and section 5 concludes.

2. Current exposure

In order to obtain an idea of critical infrastructure assets exposed to flooding hazard on the national scale, we first collect data on China’s infrastructure system. Second, we allocate users to each infrastructure asset at the local (asset) level for each sector. Upon user allocation to assets, we apply a Kernel density estimation to identify ‘hotspots’ of exposure. Fourth, flood hazard map is overlaid onto the infrastructure “hotspot” analyses. For details of methodology, which we describe briefly here, please see Hu et al. (2015).

2.1. Chinese infrastructure

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 ICT¹. Within each of these sectors, we classify sub-sectors that contain a range of different infrastructure assets (see Table 1). Overall, we collect a network-based dataset that contains a total number of 62,463

¹ Defined by the UK Infrastructure Transitions Research Consortium (UK ITRC) (Hall et al. 2012)

assets. This database represents a major part of the existing infrastructure assets that are potentially vulnerable to flooding impacts.

Table 1. Infrastructure asset datasets

Sector	Sub-sector	Asset type	Number of assets	Completeness (%)
Energy	Electricity	Power plants	2116	67
		Transmission lines (220 kv AC)	847	14 ²
	Natural Gas, Liquid and Solid Fuels	Pipelines (crude oil, natural gas, produced oil)	156	92
Transport	Roads	Roads	3752	17.9
	Rail	Rail tracks	42739	100
		Stations	5430	
	Shipping	Ports	237	4.5
	Aviation	Airports	147	80
Water	Water supply	Reservoirs	3141	100
		Dams	770	0.8 ³
Waste	Waste water	Waste treatment works	2743	100
ICT	Mass data and computation facilities	Data centres	385	Unknown

Source: adapted from Hu et al. (2014); Hu et al. (2015)

2.2. Customer allocation

We subsequently allocate a number of users to individual infrastructure asset and networks, according to a set of allocation rules. 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; D_a is the electricity consumption (in megawatts per hour) of province a; and P_a is the population of province a.

² Data for 2015.

³ Total number of dams come from InternationalRivers.org (<https://www.internationalrivers.org/programs/china>)

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. 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.

2.3. Exposure and hotspot analysis

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:

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

2.4. Flood hazard modelling

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 $0.25^\circ \times 0.25^\circ$. 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).

2.5. Infrastructure hazard exposure

In order to derive an aggregate understanding of how infrastructure hotspots are subject to flooding impacts, we impose our hotspot analyses onto the flooding hazard map and calculator those users who are exposed. For details, please see Section 3.4.3 in Hu et al. (2015).

3. Future exposure

It is well-known that a warmer climate would increase the risks of floods in China and the majority of river basins and coastal floodplains globally (IPCC 2007; IPCC 2012; Hirabayashi et al. 2013). Most climate literature have examined increasing 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 is 31–450 million people and 59 to 430 thousand km² of cropland, and the change in risk varies 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).

Although the modeling of flood hazard and exposure has improved greatly, evidence on vulnerability of societies is still lacking (Jongman et al. 2015). This is especially the case when it comes to infrastructure systems, which provide vital services to a functioning society and economy. Indeed, climate change could have substantial 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). Natural hazards, which could cause damage to national infrastructures such as energy, transport and digital communication, are projected to intensify in certain areas of the globe. The complex and interdependent nature of infrastructures provides not only the conditions for localized failures, but disruptions may propagate within and between network systems, resulting in widespread and often unforeseen damage (Thacker et al. 2017). To understand the impacts, the infrastructure risk analysis literature have studied how infrastructure systems may be vulnerable to hazards and how they may 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; Thacker, Barr, et al. 2017; Arvidsson et al. 2015). Yet little has taken climate change into account.

3.1. Future flood projection

To understand climate-change-driven flooding, inundation maps for China incorporating climate change are prepared at $0.25^\circ \times 0.25^\circ$ 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 the 2015 law. Given most assets were built before this, it is reasonable to assume the standards were designed at least within this range if not lower.

3.2. Infrastructure exposure to flooding risks

Observations revealed that both the frequency and intensity of flooding are increasing in China (Zhai et al. 1999). As China builds more infrastructures, much of which is bound to be in floodplains, exposure to flood risk may increase, though the extent of this growing risk is difficult to predict. Therefore, it is necessary to explore a set of climate scenarios to see how exposure might change. To do this, we calculate the change in flooded areas for all AOGCMs between period 1 (2016-2035) and period 2 (2036-2055), using baseline period 1986-2005. Overall, there are 132 model variations depending on which return period, the time period, RCP and AOGCM model assumptions are concerned. For each return period, we select the maximum, minimum and medium flooded area and identify its associated AOGCM at RCP 4.5 and RCP 8.5 respectively for period 1 (2016-2035) and period 2 (2036-2055). Arguably this provides the most optimistic (minimum), medium and pessimistic scenario (maximum) of changes in flooding hazard in China. We then select the model of the highest occurrence out of each set of minimum, maximum and medium scenarios of flooded extent and show the spatial variation of changing flooding – increasing, decreasing or status quo – probabilities across China, to 2035 and 2055 respectively. We show a case study of the electricity sector and its exposure to changing flood probabilities given RCP 4.5 and RCP 8.5 for the most optimistic, medium and pessimistic scenarios at return period 50. For a spatial demonstration of where hazards may change, we demonstrate a map of power plants imposed with a hazard map for model INM-CM4 – an optimistic model, for increasing flood probabilities. Detailed description with results for all infrastructure sectors will be available in an upcoming paper on the spatial variability of infrastructure exposure in the context of climate change (Hu et al. in preparation).

4. Results

4.1. Current infrastructure exposure

The integrated analysis combines flooding analyses with infrastructure vulnerability for sub-sectors including rail, aviation, shipping, electricity and wastewater (refer to Figure 1). At a provincial level, Anhui, Beijing, Guangdong, Hebei, Henan, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang⁴ exposed to flooding risks; at a city level, 66 cities are highly exposed.

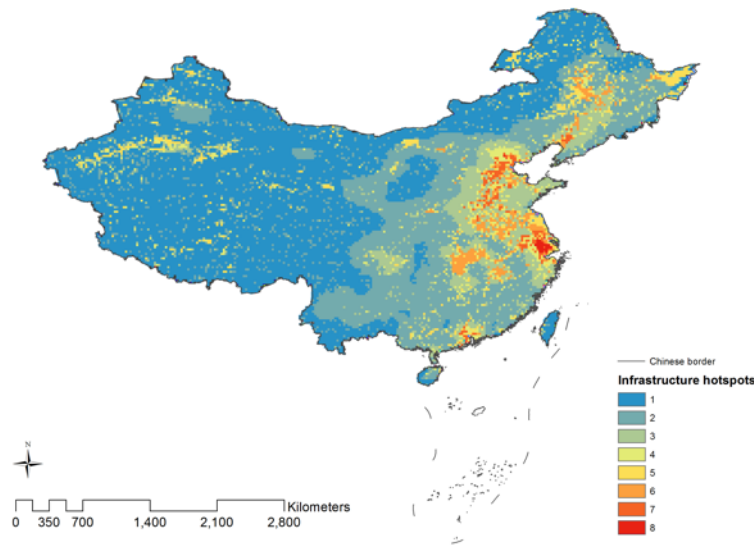


Figure 1. Infrastructure vulnerability (rail, aviation, shipping, electricity and wastewater sub-sectors) combined with flooding hazard.

4.2. Future exposure

4.2.1. Flood projection in China

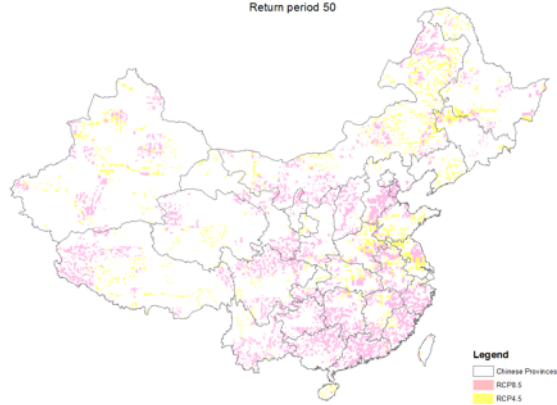
Here we show the model results for increasing flood probabilities for the most optimistic, medium and pessimistic scenarios respectively. In the most optimistic scenario, as shown in model INM-CM4 (Figure 2), we observe that flooding for RCP8.5 is heavily concentrated in south of Yangtze river, provinces experiencing significant increasing flood probabilities include Yunnan, Guangxi, Guangdong, Fujian, Zhejiang. Southern Guizhou, Hunan, Jiangxi in addition to some northern provinces such as Shanxi, Hebei, south and north Inner Mongolia and southern Gansu. For RCP4.5, there is significant spatial variation compared with RCP8.5. Increasing probabilities are in Shandong, Liaoning, north Jilin, north-east of Inner Mongolia and Hainan. By 2055, increasing flooding probabilities for RCP 8.5 “shift northward”, affecting Sichuan, Chongqing, Henan, Hubei and northern Jiangsu. For RCP4.5, most increasing hazard lie in north-eastern Inner Mongolia and the northern border of Jilin with Heilongjiang.

⁴ Exceptionally exposed is defined as provinces that are located in areas where their infrastructure hotspot values are either 7 or 8.

Model: INM-CM4 – most optimistic scenario with least flooding extent

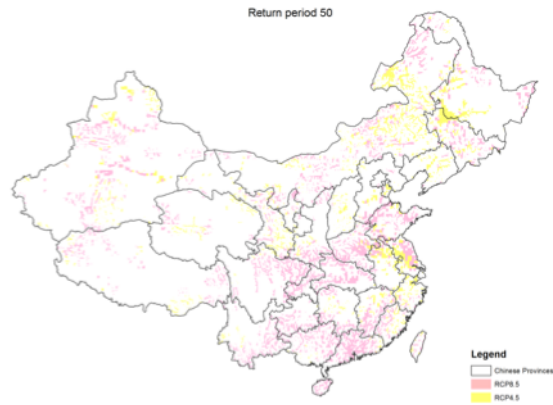
1986-2005 and 2016-2035

Return period 50



1986-2005 and 2036-2055

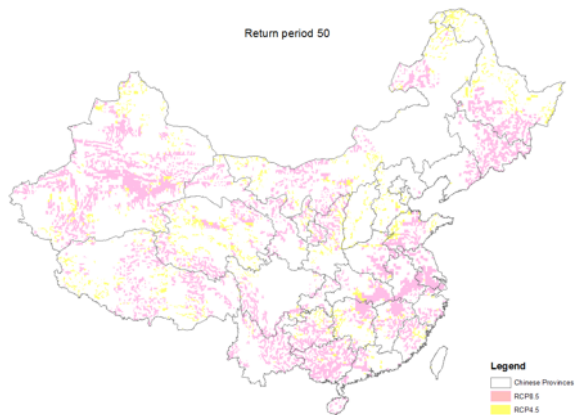
Return period 50



Model: MPI-ESM-LR. Medium scenario.

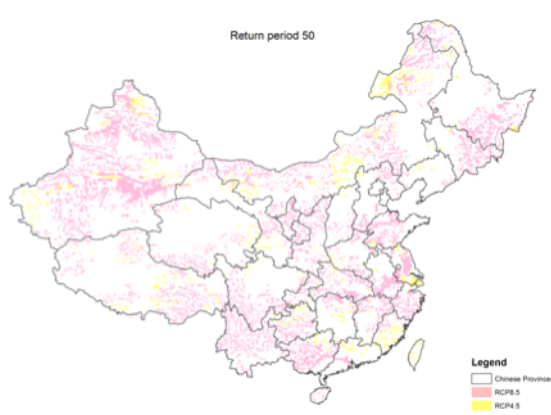
1986-2005 and 2016-2035

Return period 50



1986-2005 and 2036-2055

Return period 50



Model: MIROC5. Worst scenario with the highest flooding extent

1986-2005 and 2016-2035

1986-2005 and 2036-2055

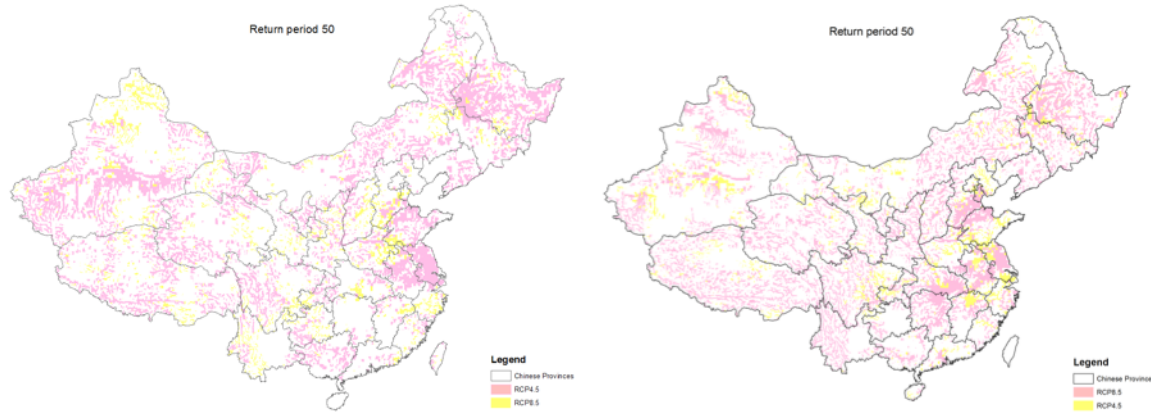


Figure 2. spatial demonstration of increasing flood probabilities for models INM-CM4, MPI-ESM-LR and MICROC5 at RCP 4.5 and RCP 8.5 respectively.

In the medium scenario (model MPI-ESM-LR), increasing flood hazard under RCP8.5 are concentrated in Yunnan, Guangxi, the borders between Hunan, Hubei and Jiangxi, southern Anhui and Jiangsu. Compared to the optimistic scenario, Jilin and southern Heilongjiang face increasing probabilities. For RCP4.5, flooding hazard is mostly in northern Heilongjiang and Hebei. By 2055, flooding hazard escalate in large parts of Tibet and Xinjiang, Inner Mongolia, Yunnan and particularly in Ningxia, Shaanxi, Hubei and Chongqing for RCP8.5. For RCP4.5, Inner Mongolia suffers notable worsening flood risks.

In the worst scenario (MIROC5), northeast China (the borders between Inner Mongolia, Heilongjiang and Jilin), eastern China (Shanxi, Shandong, Hebei and northern Anhui), western China (Sichuan, Chongqing, Xinjiang Tibet) are face increasing flood hazard under RCP8.5. By 2055, the majority of China's land areas is at increasing probabilities for RCP8.5 except for eastern Guizhou, eastern Yunnan, southern Jiangxi, north-eastern Inner Mongolia. On the contrary, for RCP4.5, most areas at increasing flood hazard are concentrated in Jiangsu, Anhui, Shandong and western Heilongjiang. By 2055, increased flood areas escalate around these regions and extend to Hubei and Hunan.

4.2.2. Infrastructure exposure to climate-induced flooding hazard – the case of electricity sector

Given the range of scenarios we observed above, the same existing infrastructure stocks' exposure to changing flood hazard will alter. Figure 3 shows the exposure the percentage change of power plants exposed to increasing flood probabilities at return periods 30, 50, 100 by 2036 and 2055 respectively. We observe that, regardless of the scenario (optimistic, medium or pessimistic), more assets will face increasing flooding probabilities in general. For power plants, the range of assets exposed to increasing flooding probabilities is 4%-20%, 9%-25%, 14%-32% for optimistic, medium and pessimistic scenarios respectively. Table 2 identifies what the assumption was for each ring in Figure 3. We demonstrate the spatial distribution of power plants imposed with an optimistic scenario of increasing flooding probabilities in Figure 4. We can see quite a number of power plants located along the coast are exposed to increasing flood hazard by 2036. Detailed results for all infrastructure sectors will be available in an upcoming paper on the spatial variability of infrastructure exposure in the context of climate change (Hu et al. in preparation).



Figure 3. Power plant exposure changes of increasing flood probabilities under low, medium and high scenarios, representing optimistic, medium and pessimistic respectively.

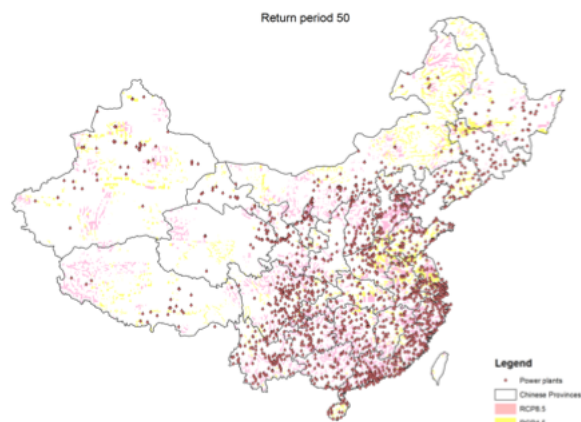


Figure 4. Location of power plants exposed to the optimistic scenario of flooding by 2036.

Table 2. Ring number assumptions in Figure 3

Ring number	Return period	Time period
1	30	(1986-2005) and (2016-2035)
2	50	(1986-2005) and (2016-2035)
3	100	(1986-2005) and (2016-2035)
4	30	(1986-2005) and (2016-2035)
5	50	(1986-2005) and (2016-2035)
6	100	(1986-2005) and (2016-2035)
7	30	(1986-2005) and (2036-2055)
8	50	(1986-2005) and (2036-2055)
9	100	(1986-2005) and (2036-2055)
10	30	(1986-2005) and (2036-2055)
11	50	(1986-2005) and (2036-2055)
12	100	(1986-2005) and (2036-2055)

5. Conclusions

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 ICT infrastructures due to extreme flooding. We also demonstrate the potential changing exposure and vulnerabilities arising from climate change for the Chinese electricity sector, the results of which can be useful in informing the long-term planning and development of climate resilient infrastructures in China. Future work will extend to other infrastructure sectors such as transport, water, waste and ICT and comparing the results from all other 11 AOCGMs, the results of which are available in an upcoming paper spatial variability of infrastructure exposure in the context of climate change (Hu et al. in preparation).

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