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# **Too Big to Fail? The Spatial Vulnerability of the Chinese Infrastructure System to Flooding Risks**

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## **ABSTRACT**

Analysis of vulnerability to climate-related hazards such as flooding typically starts with the distribution of people and economic assets in flood-prone locations. However, this approach provides limited information about the severity of disruption that may be caused in extreme and disastrous events, as it does not fully account for the economic and social dependence on vulnerable assets. Infrastructure assets are particularly significant in this regard because of the very high social and economic dependence on these systems, which can extend far outside the hazard zone. 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. We apply the methodology to the rail and electricity sectors. The results show the locations of critical infrastructure that is exposed to risk of flooding on a broad scale. We are also able to calculate the potential number of customers affected should infrastructure assets fail owing to one or a series of flooding event(s) on a local scale. Although interestingly our results show that the critical infrastructure in these sectors is not exposed to high flooding risks, however, climate change may increase the frequency of flooding events in these locations and planners should at least investigate the flood defence structures in these areas.

## **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 2 provides the conceptual framework we adopt in understanding the infrastructure system and spatial maps of infrastructure asset locations. Section 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 discusses some preliminary results, implications and possibilities for future work.

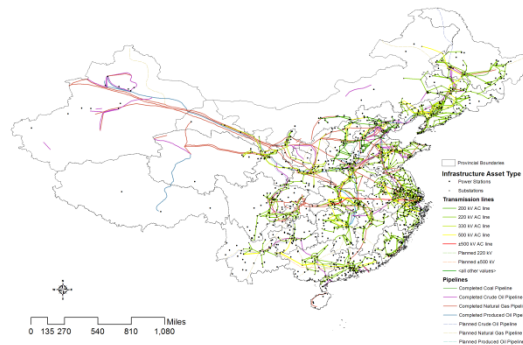
## 2. INFRASTRUCTURE VULNERABILITY IN CHINA

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 ICT, as defined by the UK Infrastructure Transitions Research Consortium (UK ITRC) (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 1). 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.

**Table 1 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 1 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).

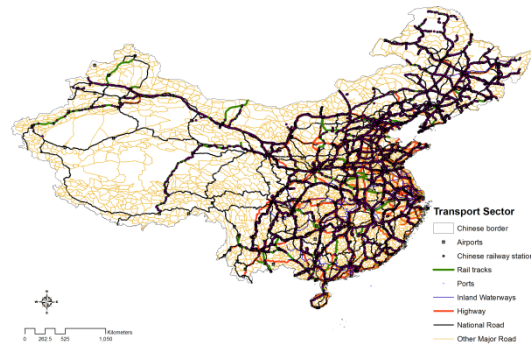


Source: Harvard ChinaMap, Carbon Monitoring for Action (CARMA) and CNTEN.Ltd

Figure 3 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<sup>3</sup>, which compared with 2010 decreased by 169.1 billion m<sup>3</sup> (*Ibid*).

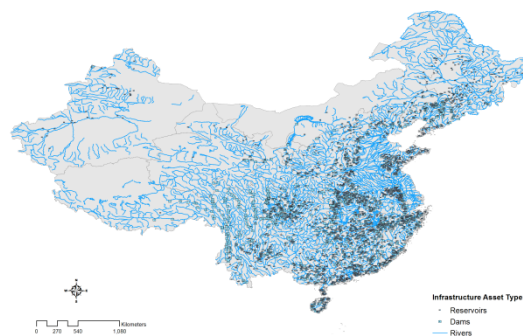


**Figure 2. The Chinese Transport Network**

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

Figure 4 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.

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).

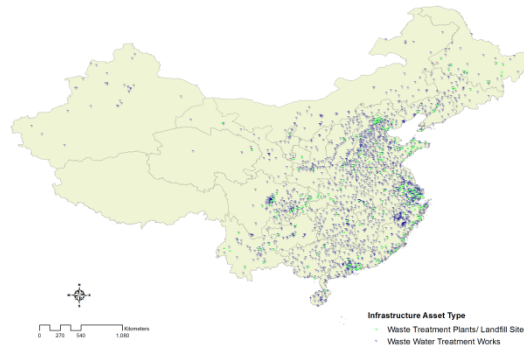


**Figure 3. The Chinese Water Sector**

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

Figure 5 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 4. The Chinese Waste Sector**  
Source: Chinese Ministry of the Environment (2012)



**Figure 5. The Chinese ICT Sector**  
Source: the China Internet Data Centre (IDC) database.

### 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.

#### 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 2).

**Table 2. 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

### 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:

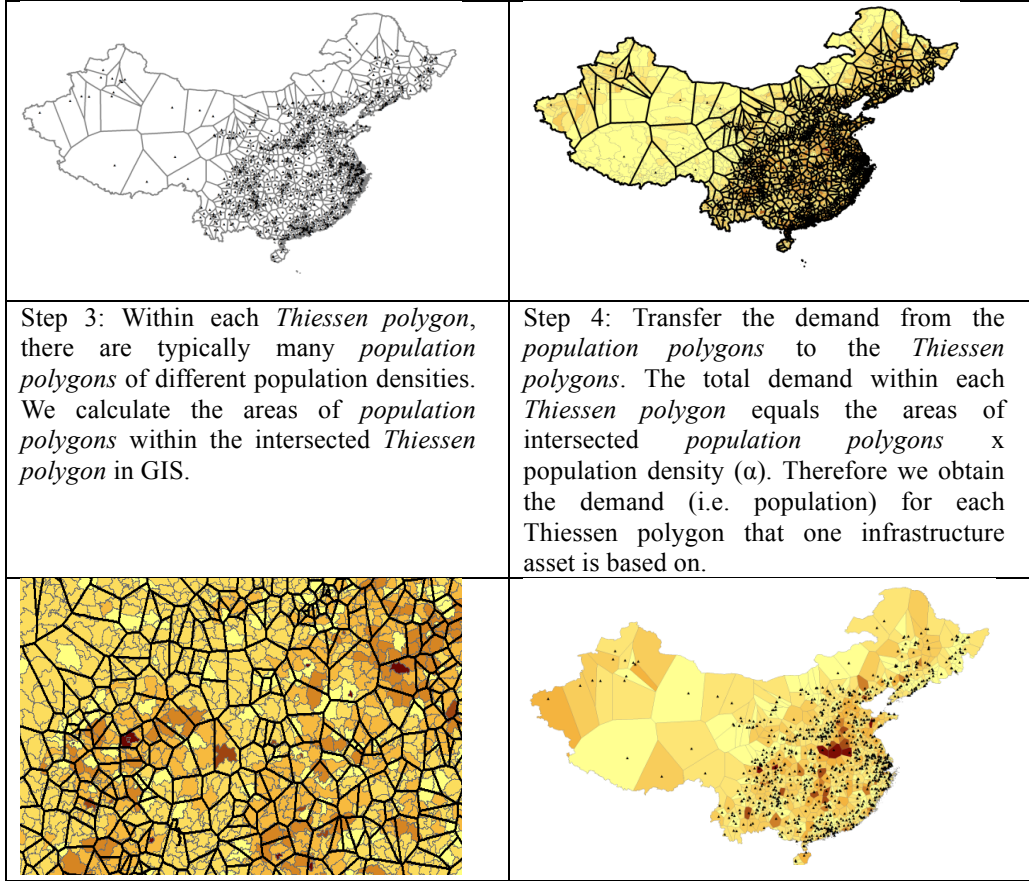
- The customers we allocate to each power plant must be closest to that plant than any other in the surrounding area.
- The number of customers served by any power plant is proportional to its capacity. In other words, all power plants of the same capacity serve roughly the same number of customers.

#### 3.2.1. 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 ( $\alpha$ ) for each county and multiple  $\alpha$  with the intersected regions for each infrastructure asset (see Table 3). Thus, for each region the asset is located in, we have a preliminary customer footprint that is reliant on the infrastructure asset.

**Table 3. Preliminary customer allocation by Voronoi diagram in GIS**

Step 1: Build a Voronoi diagram ( <i>Thiessen polygons in GIS</i> ) with plant locations.	Step 2: Overlay the <i>Thiessen polygons</i> with county <i>population polygons</i> . Within each <i>population polygon</i> , we calculate the population density ( $\alpha$ ) by dividing the population with its area.
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Source: adapted from ET Geo Wizards, 2013

### 3.2.2. 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,  $A_1, \dots, A_n$ , with populations  $p_1, \dots, p_n$ , respectively, to  $m$  power plants,  $P_1, \dots, P_m$  with capacities  $c_1, \dots, c_m$ , 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  $d_{i,a} < \dots < d_{i,E}$ , and we allocate counties  $A_a, \dots, A_z$  to power plant  $P_k$ , so  $P_k$  serves a population of  $p_k = p_a + \dots + p_z$ . 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  $\mu$  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  $< \mu$  (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  $> \mu$  (not enough people):
    - 3.1. Find county,  $A_c$ , that is closest to  $P_k$  but is not one of the counties  $A_a, \dots, A_z$  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  $\frac{1}{m} \sum_{k=1}^m \sum_{i=a}^z d_{i,k}$ .
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### 3.3. Hot-spot analysis using Kernel density estimation

Following customer allocation for each infrastructure asset that satisfies the two conditions set out in section 3.2, 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<sup>2</sup>. 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  $e_{ij} \forall j \leq n$ . 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.

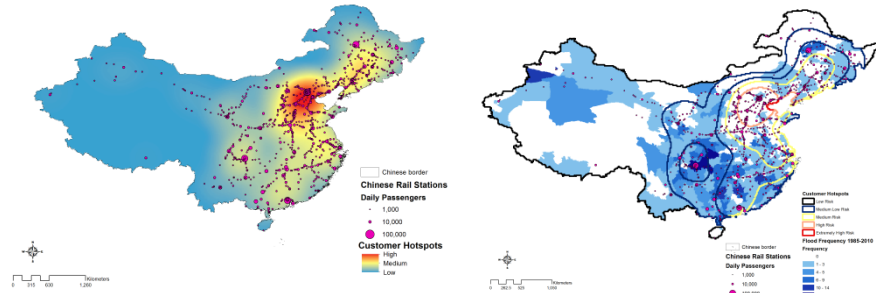
### 3.4. Impose flooding frequency map on the hot-spot analysis

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 hotspots i.e. where customers are concentrated might be vulnerable to flooding impacts.

## 4. RESULTS AND DISCUSSION

We apply our methodology to the rail and electricity subsectors. For the rail subsector, we identify some stations in the southwest that are exposed to high levels

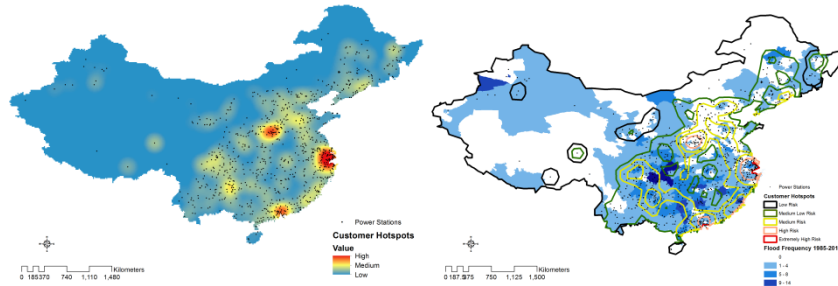
of flooding risks. The concentration of customers (1,779,000) in the northeast where hotspots are identified, is not located in cities where flood frequency is the highest.



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, 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



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.

## 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 1 and study the network effects influence the propagation of infrastructure failure when flood hazards materialize.

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## References

- 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. *China Electric Power Yearbook*, China Statistics Press.
- Civil Aviation Administration of China, 2013. 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](http://www.caac.gov.cn/i1/K3/201303/t20130325_54626.html) [Accessed November 28, 2013].
- CNTEN.Ltd. (2013). CNTEN: China Oil and Gas Pipelines and Distribution Plans. Retrieved November 20, 2012, from <http://www.cnten.com>
- 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](http://www.ian-ko.com/ET_GeoWizards/WhitePapers/gw_allocating_demands_to_services.htm) [Accessed November 28, 2013].
- Hall, J. et al., 2012. *A Fast Track Analysis of strategies for infrastructure provision in Great Britain*.
- The Havard WorldMap Project. (2014). Harvard ChinaMap. Retrieved October 01, 2013, from <http://worldmap.harvard.edu/chinamap/>
- KPMG, 2009. *Infrastructure in China : Foundation for growth*.
- Lehner, B., R-Liermann, C., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., Döll, P. *et al.*: High resolution mapping of the world's reservoirs and dams for sustainable river flow management. *Frontiers in Ecology and the Environment*. Source: GWSP Digital Water Atlas (2008). Map 81: GRanD Database (V1.0). Available online at <http://atlas.gwsp.org>
- 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](http://www.mohurd.gov.cn/zcfg/jsbwj_0/jsbwjcsjs/201101/t20110106_201873.html) [Accessed November 28, 2013].

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> [Accessed November 28, 2013].

Ministry of Rail, 1980. *Classification of Chinese Railway Stations* 《铁路车站等级核定办法》.

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> [Accessed November 28, 2013].

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](http://www.moc.gov.cn/zhuzhan/tongjigongbao/fenxigongbao/hangyegongbao/201104/t20110428_937558.html) [Accessed November 28, 2013].

Ministry of Water Resources, 2011a. *Bulletin of Flood and Drought Disasters in China* (中国水旱灾害公报) .

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](http://www.mwr.gov.cn/zwzc/hygb/szygb/qgszygb/201212/t20121217_335297.html) [Accessed November 28, 2013].

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://zfxgk.nea.gov.cn/auto86/201212/W020121203312244945303.pdf> [Accessed November 28, 2013].

National Geospatial-Intelligence Agency. (2013). World Port Index. Retrieved June 02, 2013, from <http://hdl.handle.net/IGA/11237>

Ummel, K. 2012. CARMA revisited: an updated database of carbon dioxide emissions from power plants worldwide. Center for Global Development, Working Paper 304.

Wheeler, D. and Ummel, K. 2008. Calculating CARMA: global estimation of CO<sub>2</sub> emissions from the power sector. Center for Global Development, Working Paper 145.