Accumulation pattern of construction materials and its socio-economic drivers in Chinese urban buildings

（中国の都市建築物における建設資材の蓄積パターンと社会経済要因）

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Summary

In the cycle of resources and energy extracted from nature, transformed into beneficial products through industrial process, then consumed and used to meet various demands, and finally returned to the nature as waste, socio-economic activities have double negative environmental impacts: resource extraction and waste emission. Reducing them is one of sustainable development goals, however, it is particularly difficult for developing countries which are facing many other socio-economic development issues. How to harmonize the development and sustainability is the big question here. As an overwhelming process taking place in China in the recent decades, urbanization has benefited the people life and promoted regional economic growth, but brought out more intensive resource extraction for city construction. Decoupling such socio-economic development from material accumulation and full use of secondary resources stocked in cities are necessary toward sustainable development. To achieve it, understanding the evolution patterns and composition of material stock and flows, as well as its drivers, is a prerequisite. Existing literature focused on country and province level, but not yet for city level although the city plays a key role in sustainability as a major consumer of materials and energy. And cities might have different evolution patterns and present status affected differently by socio-economic factors, which should be taken into account when to make urban sustainable decisions, but not well examined.

To fill these gaps, this study presents the major construction materials stocked in Chinese buildings at city level and their patterns along with socio-economic development using both dynamic and static bottom-up method with statistical data and GIS data respectively. It reflects different challenges and common problems in development and sustainability of urban buildings sector, and addresses discussion of how cities move forward to sustainable development.

The thesis commences with a chapter of introduction, presenting an overview of the practical and theoretical background to this research followed by an elaboration on the motivation and problem statement of this thesis, as well as the research question, scope and thesis structure.

Chapter 2 introduces the theoretical foundations of industrial ecology as an interdisciplinary field and socio-economic metabolism (SEM). As a widely used methodology to investigate the SEM, the material flow analysis (MFA) is generally introduced and its principles are summarized in several dimensions. A descriptive and critical literature review is conducted on Chinese material stock and flows research using the bottom-up method so far.

Chapter 3 explains the general bottom-up method of MFA, followed by the description of static manner. Dynamic manner is then elaborated from model generalization to its involved

parameters and assumptions. And Perpetual Inventory Method (PIM) from the field of economics is introduced and compared with conventional dynamic MFA. This section is closed with discussion of a key parameter in bottom-up analysis - material intensity.

Chapter 4 provides an overview of the pattern, change and drivers of material accumulation in buildings of Chinese cities. The PIM was adopted for a bottom-up material stock (MS) estimation of buildings in 215 Chinese cities from 2000 to 2015. Throughout this period of time, the total construction materials stocked in urban buildings almost tripled, and more construction materials investments flowed into non-residential buildings. The urban building MS in 35 major cities generally accounted for almost half of the total MS. At per capita level, it overall increased from 47.3 tons per person in 2000 to 77.9 tons in 2015. Per capita buildings MS in 35 major cities are always higher than the rest of other cities and such gap has been widened especially in non-residential stock. Based on buildings MS estimations of each city, empirical panel regression shows urbanization positively correlated with urban building MS and overall it explains most of its growth. The threshold regression model examined the non-linear effects of urbanization on MS accumulation under different economic development levels. In economically underdeveloped areas or stage, more construction materials are required for the process of urbanization. When the economy develops to a certain extent and there has been a certain amount of capital accumulation, the elasticity of urbanization on stocks would decrease. This draws out a discussion on resources management for different cities. For those economically underdeveloped cities, long-term urban planning, efficient use of resources, and building designing may be the top priority to reduce the environmental impacts for future necessary city construction. While in the wealthy regions, they may no longer face the problem of urban construction in the future, instead, stock and waste management can be their challenge. Before the relevant policy is formulated, the quantity, composition and spatial distribution of current building material stock is necessary to fully understand and study.

Chapter 5, therefore, the building MS for the 14 wealthy cities of Eastern China was calculated with GIS-based static bottom-up method of year 2017. In total, 7.9 Gt materials are stored in a total area of 3,790 km^2, resulting in an average density of 2.1 Mt/km^2. A hotspot analysis of the material stock distribution was performed, identifying and providing maps of the clusters and location of the MS which are more likely to produce large quantities of demolition waste and demanding more materials in case of maintenance and retrofitting. The per capita building MS is positively correlated with per capita GDP, informing developed cities should focus on reuse and recycling strategies regarding demolition waste, while policy makers from still-developing cities should take into account the environmental impacts related to economic growth, which is consistent with above empirical regression results.

Chapter 6, to better investigate the trends and change of construction material flow and stock over space and time along with socio-economic development, and find how to tackle conflicts between development and sustainability, building-by-building the material flows and stock accumulations was chronicled in high-resolution 4d-GIS database for the Tiexi district of Shenyang, a microcosm of China's urban transformations since the early 20th century. 42 million tonnes of construction materials were needed to develop the study area from 1910 to 2018, and 18 million tonnes of material outflows were generated by end-of-life building demolition. However, over 55% of inflows and 93% of outflows occurred since 2002 during a complete redevelopment of the district. Only small portions of end-of-life materials could have been reused or recycled because of temporal and typological mismatches of supply and demand and technical limitations. Analysis reveals a dramatic decrease in median building lifetimes to as low as 6 years in the early 21st century. These findings contribute to the discussion of long-term environmental efficiency and sustainability of societal development through construction, and reflect on the challenges of urban renewal processes not only in China, but also in other developing and developed countries that lost (or may lose) their traditional economic base and restructure their urban forms.

Chapter 7 summarizes the different research aspects presented in the previous chapters into a combined study. Implications for development and sustainability of the research are discussed, for China, for developing countries as well as for the whole world. Finally, research limitations and directions for further research are raised.

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1. Introduction

1.1 Research background

(1) Double environmental impacts by human activities

Throughout the anthropogenic history, human activities have always depended on the natural environment. Resources and energy are extracted from nature, transformed into beneficial products through industrial process, then consumed and used to meet various demands, and finally returned to the natural environment as waste, shown in Figure 1. In this linear course, apparently, socio-economic development has double impacts on environment: resource extraction and waste emission. The former changes the natural cycle of materials and substances, and leads to ecosystem deterioration. For example, the mining usually leaves indelible and irreversible "scars" on the earth, accompanied with vast amount of hidden flow. The latter results in environment pollution due to immoderate waste disposal. However, these issues were not such severe and urgent until the advent of the industrial revolution. In particular, during the following industrialization and urbanization in advanced regions, technological innovation has greatly increased labor productivity, and on the other hand, people required better quality of life. Therefore, natural resources have been input into anthroposphere at a much faster rate to obtain more economic wealth and complete the urban infrastructure, thus enormous materials accumulated in society. Simultaneously, attendant waste is more generated challenging the city management.

Among the environmental issues we face today, climate change attracted attention due to its worldwide impact. The paradigm of climate change mitigation and adaptation was proposed to address it. Analogously, there are also two general directions on how to reduce the doubles impacts for general environmental matters: reducing unnecessary material input and output (dematerialization, slowing down the material metabolism in society), and reasonable waste disposal. This is in accordance with 3R principles, which emphasized reduce, reuse and recycle, particularly in the context of production and consumption. The related concept of the circular economy (with aims including keeping resources economically active e.g., by recycling) is official policy in China (Deutz and Ioppolo 2015).

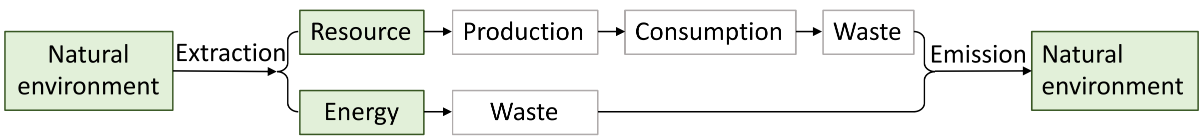


Figure 1 Double environmental impacts in linear industrial process

(2) Material stock and flows

After extracted physical materials entered economy system as the input, some is consumed and transformed into waste and emissions the moment their embedded energy is used, like fossil fuels and foods. They provide the service or function only when they are consumed, accordingly, they are not staying in the society for years. While minerals and metal materials can be used for long time as products through manufacturing, assembling, etc. They are also called as fixed capitals in the domain of economics, which by definition are stocked in society and can give constant service for a long duration. When aged stock does not serve any more owing to economical or physical reason, they retire from the stock and flow back into nature as solid waste. The stock not only drives material flows during use, maintenance and at the end of their service lifetime (Wiedenhofer et al. 2015), but also drives the energy flows for their operation and working. Furthermore, it entails temporal and spatial lock-ins on energy use and emissions due to long useful duration (Lanau et al. 2019). And stock is regarded as a reservoir of secondary materials if its waste was carefully managed. Hereby, material stock in the form of buildings, infrastructures and machinery plays essential role in the socio-economic metabolism. In order to reduce the double environmental impacts caused by stocks and flows, how to prolong the service lifetime, how to fully and efficiently use them, and how to recycle the retired stock becomes researchers' concerns. But present status of material stock and related metabolism should be well studied first.

Material stock and flows are usually to link with economic indicators in the frame of IPAT identity, where the environmental impacts (I) are the results of effects from population (P), affluence (A) and technology (T). When world population expands and affluence grows, enhancing the technology and resource productivity is the only way to achieve decreasing the environmental impacts. Therefore, examining the resource efficiency/productivity is beneficial for investigation of our sustainable development progress. It has been figured out that material use productivity grows, stock productivity not yet (Krausmann et al. 2017), which informs the stock in society still keeps constant accumulation along with the economic growth. How to decouple the stock from economic progress deserves more research concerns.

(3) Construction materials

The major component of the stock, buildings and infrastructure, has been piled with huge amount of construction materials, including steel, cement, aggregate, timber, etc. They are second only to water as the largest material flows into urban areas by mass (Krausmann et al. 2017), and the top waste deposit (Augiseau and Barles 2017). The mining, production, and use of virgin construction materials are considerable forces of global environmental impacts, including greenhouse gas emissions (Hertwich 2019), altering landscapes and geographical features, land use change, and generation of massive tailings, overburdens, and toxic byproducts (Augiseau and Barles 2017; Lanau et al. 2019; Moriguchi and Hashimoto 2016).

However, when construction materials are released from end-use built environment, they are potential to be reused. Theoretically, for specific materials high potential for circularity could have been achieved. Steel can be recycled with relatively high rate as it performed in practicality (T. Wang et al. 2015a). Most sand and gravel are embedded in concrete scraps. Crushed concrete can be incorporated into new concrete, albeit with limits as its addition degrades performance, and fresh cement is still required. Early planning and measures for the circularity of demolished waste should be worked out, which can be supported by the mapping and quantifying of the resources in buildings.

(4) Urbanization in China

Urbanization, the process of population concentration from rural to urban area, promotes the socioeconomic development though the economics of agglomeration (Henderson 2002). While urbanization brings social and economic benefits to cities, it also makes cities take on unprecedented challenges on infrastructures. In the past two decades China experienced a period of rapid urbanization, seeing its urban population go from 18% in 1978 to 29% in 1995, and reaching 57% in 2016. According to the 13th Five-Year Plan (2016-2020), adopted in March 2016 by the People's National Assembly of China, urban population is expected to reach 60% by 2020. However, as early as the 1950s, urbanization in the Japan and United States reached more than 60%, coming to 91% and 82% respectively in 2016. In other words, more than half of the population of China lives in urban areas to this date and this trend will continue in the foreseeable future and close the gap with developed nations. This massive migration from rural to urban areas require huge capital investments and extensive construction activities, as it has been seen in recent studies on material flows (Schandl et al. 2017; Miatto et al. 2017) and stocks (Krausmann et al. 2017).

Beyond the obvious figures indicating population aggregation into cities, renewal, redevelopment or regrowth (of old residential blocks and old industrial base, etc.) are taking place inside of cities as well, as many developed cities implemented in since the 1970s (Z. Han et al. 2019). Inevitably, a substantial part of new constructions is required to increase city attractiveness and economic vitality. Either with the rapid gathering of urban population or changes of internal structure in cities, urbanization will undoubtedly bring considerable pressure on resources and the environment.

1.2 Problem statement

How to reduce above double environmental impact is particularly difficult for developing countries which are facing many other social development issues. They are striving to become "better" in both social and economic development which developed countries have achieved with consuming huge amount of materials, at the same time, they are also expected to achieve environmental-friendly sustainability. So how to control the environmental impacts caused by rapid development is the big question here.

Cities are key places determining whether sustainability can be achieved because urban settlements consume 70-80 percent of all resources on a global scale (Baccini 1997), which is enhanced by urbanization. As an overwhelming process taking place in China in the recent decades, urbanization has benefited the people life and promoted regional economic growth, but brought out more intensive resource extraction used for city construction. China is currently said as the single most influential driver of the global growth in demand for construction materials. China constructed 2.7 billion m^2 of building floorspace every year since 2000 (EPS 2017) along with rapid growth of transport and other civil infrastructure. It becomes possessor of the largest building stock in the world and is poised to continue being responsible for much of the global demand for construction materials to at least 2030 (Dean, B., Dulac, J., Petrichenko, K., and Graham 2016). In other words, it is an inevitable trend to have constant resources input in foreseeable future. Additionally, as an important part of urbanization, urban renewal changes urban morphology and function, inevitably dictating material stock and flow dynamics in cities around the world. Redevelopments are characterized by large-scale demolition in China (Deng, Chen, and Liu 2017), generating large amounts of construction and demolition waste (CDW) (Wu, Duan, et al. 2016) whose treatment involves multiple environmental challenges and which place great burdens on finite landfill space (Zhao, Leeftink, and Rotter 2008). Rapid, ubiquitous redevelopment results in extremely short building lifespans of only 20-40 years in Chinese cities (J. Wang, Zhang, and Wang 2018; Cao et al. 2019; Deng, Chen, and Liu 2017; Cai et al. 2015). Thus, development and sustainability seem not compatible with each other. Seeking for a sustainable development way should commence with understanding the past pattern and present status.

Regarding the constructions and corresponding environmental impacts, decoupling socioeconomic development from material accumulation and full use of secondary resources stocked in cities are possible measures toward sustainable development. To achieve it, we firstly need to answer two questions: (1) which pattern did material stock evolve in and what drives its accumulation? (2) how much, where and what composition is the present material stock? They have been focused by existing literature on country and province level, but not yet for city level.

Furthermore, there are great variations in the vast territory of China, leading to regional disparity and unbalanced development. The rapid urbanization has been accompanied by excessive concentration of urban population in megacities (Henderson 2002), which are also responsible for large part of material accumulation in the last decades. While smaller-sized cities still require enormous resources investment for growing urban population in the future. Therefore, they might have different evolution patterns and present status which are affected differently by socio-economic factors and should be taken into account when to make urban sustainable decisions, but not well examined yet. Of course, they also face some common urban development problems with intensive environmental impacts, like urban redevelopment, which were rarely discussed.

1.3 Research objectives

The research aims to reveal the material metabolism in buildings and the socio-economic drivers that dictate the accumulation of material stock at the city level. Understanding the evolution patterns and drivers for different cities is expected to help make appropriate local policy of resource conservation and waste disposal. This research especially plans to fill these gaps by identifying the impact of urbanization on past pattern of building material stock and flow to understand future material requirement and second resource potentials. Explicitly spatial distribution of material stock is highlighted for providing early warning of waste management.

The research question is:

What is accumulation pattern of construction materials and its socio-economic drivers in Chinese urban buildings?

This question can be broken down into the following sub-questions:

1. What are the patterns of building material accumulation in cities?
2. What are the drivers of building material stock accumulation?
3. What is the role of urbanization in building material stock accumulation in different cities?
4. What is the present status of building material stock in developed cities?
5. How does urban development impact on material metabolism of urban building?
6. What kind of strategy should be urgently commenced to implement?

1.4 Scope and limitations

The scope of this research is the major construction materials stocked in Chinese buildings at the city level and their evolution patterns along with socioeconomic development. The major limitation in general material flow analysis and industrial ecology, as well in this study, is data. In the review of existing literature in section 2.3.3, Chinese cases were developed mostly for the whole nation, municipalities or provinces owing to the available data for those large administrative unit. City-level research, however, is rare. China is a nation with a vast territory and many cities, moreover, there is heterogeneity in the methods and structures of data statistics among cities and provinces. Thus, data collection and compilation become more time-consuming and complex. And even if we make great efforts and take much time for it, many data are very likely missing. It seems impossible to do material metabolism analysis for all cities. This study commences with building materials stock estimation for over 200 cities from 2000 to 2015. Although with considerable time on data collection, necessary assumptions and data conversion are processed to derive the adjusted data for model.

The GIS data is scarcer when to investigate the spatial distribution of material stock in Chapter 5 and 6. Basically, original GIS data includes pure geographical information exclusively, without detailed buildings attributes needed for material stock estimation. Other sourced-data can supplement the GIS data but they are stored in different data structures, so that to integrate them into a unified database is another big challenge and can result to artificial errors. This limitation is especially reflected in Chapter 6 using 4d-GIS, where its obstacles are more discussed.

1.5 Structure of thesis

The thesis commences with an introductory chapter and a chapter of literature review. The following chapters would unpack their corresponding methods, data, results and conclusions based on the research flow. With implications on practice and theory, a discussion and conclusion would close this research. The details of each chapter are described below.

Chapter 1 presents an overview of the practical and theoretical background to this research followed by an elaboration on the motivations for focusing on the topic of material metabolism of urban buildings in this thesis, as well as statement of main research question and sub-questions.

Chapter 2 starts with a discourse about the theoretical foundations of this thesis from the view of ecology. Industry ecology is introduced as interdisciplinary field, followed by a theory of socioeconomic metabolism. As a widely used methodology, the material flow analysis is generally introduced and its principles are summarized from several dimensions. A descriptive and critical literature review of research is conducted on the subject of material stock and flow so far.

Chapter 3 explains the bottom-up method, followed by the description of static material stock analysis. Dynamic manner is elaborated from model generalization to its involved parameters and assumptions. And Perpetual Inventory Method is introduced and compared with conventional dynamic material flow analysis. Finally, this section is closed with discussion of material intensity.

Chapter 4 focuses on pattern of urban building material stock and flow of 215 cities from 2000 to 2015 and its change though the Perpetual Inventory Method. The parameters and material intensity are elaborated, and then put into model considering the uncertainty by the means of Monte Carlo simulation. Based on buildings material stock estimations, econometric models of panel regression and threshold regression are employed to examine the socioeconomic drivers, especially the impact of urbanization on stock accumulation for cities at the different developing stages.

Chapter 5 describes the GIS-based method to understand the amount, composition, and location of current building material stock in urbanized mega cities, providing the information for early warning and design appropriate strategies of demolition waste management for an environmentally sustainable society.

Chapter 6 analyzes the construction material flow and stock trends that shaped and were shaped by the development, decline, and renewal of cities. The Tiexi district of Shenyang is taken as a case study, a microcosm of China's urban transformations since the early 20th century. The findings contribute to reflect on the challenges of urban renewal processes not only in Chinese cities, but also in other developing and developed countries.

Chapter 7 summarizes the different research aspects presented in the previous chapters into a combined study. Finally, directions for further research are raised.

2. Theories and state of the art

2.1 Theoretical foundations

2.1.1 Industrial ecology and sustainability

Looking back on the course of human environmental protection, the principles and methods have undergone a long historical evolution (Figure 2). End-of-pipe treatment is the pioneering environment strategy by implementing effective treatment to the pollutants at the end of the production process (Franklin 1995; Saavedra et al.2018). Although the environment pollution caused by industry production had been reduced to a certain extent, it is impossible to enable a complete control, and it does not involve the perspective of effective resources use. To thoroughly solve the pollution problem, process control on generation of pollution is required. Cleaner production thus calls for reducing waste generation during the whole life cycle of product production and service, emphasizing the control from the source. Subsequently, a more systematic concept of circular economy was proposed, which analyzes the economy through analogy it to the material and energy flow in natural ecosystem. Industrial ecology is one school under this umbrella concept (Reike, Vermeulen, and Witjes 2018; Korhonen, Honkasalo, and Seppälä 2018; Ehrenfeld 2004; Saavedra et al. 2018), a systematic study of resources flows in industrial and consumption processes, their environmental impacts and socioeconomic drivers (Clift and Druckman 2015), aiming to investigate and monitor the environmental issues of society and find solutions toward the sustainability. Industrial ecology was "born" in the industrial production process, as happened in metallurgical plants for example. University researchers realized its significance and developed it beyond the secondary industrial to the entire industry and society.

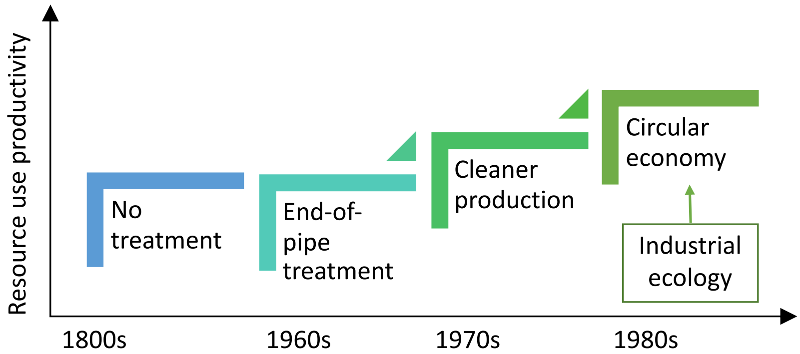


Figure 2 Evolution of the principles and methods for environmental protection

Industry ecology is an interdisciplinary science for studying the sustainable development. In particular, industrial ecologist focus on specific system linkages in the global social ecological system, which is a complex system with many actors, causal loops, economic and physical effects. No discipline can study it all, what a discipline can do is to select certain scopes in the system that it has identified as important and can study those from a scientific perspective and offer the insights to other disciplines and to broaden the societal discourse. This is exactly what industrial ecology does as well. The core scopes studied with methods in industrial ecology are listed in Figure 3 edited based on (Pauliuk et al. 2017). The first one, coproduction and waste utilization are core industrial ecology concept, actually the whole notion of industrial ecology stems the idea that one industry's waste should be another industry's raw materials. So how big are the resources and emissions savings when using waste as a feedstock for industrial production is one of typical questions that are studied when look coproduction and waste utilization. Basically, all industrial ecology methods are fit for doing that.

Materials cycle research devoted on the investigation of societal stocks and flows of a certain material and how this metabolism evolves in space and time. It also enables to answer how much materials we need to build up and expand in-use stocks (buildings, infrastructure, products), and how much scrap will be available in the future, and at which quality. For example, how large are the steel stocks and residential buildings and how much can we recycle from torn down residential buildings in the future. Material cycles are of course studied using material flow analysis but also life cycle assessment can have an important say here especially when we want to link material cycles to energy consumption and environmental impacts.

Industrial ecology also studies the service-stock-flow, where the typical questions are: how big is the impact of different efficiency strategies on the link between service provision and environmental impact, how can services be provided with less? Fewer products, less material, less energy, and if material and energy flows decouple from socioeconomic development, improved life quality or well-being. For example, what is the resource requirement of the energy transition, how much steel and aluminum do we need to build all the wind turbines and solar panels to then generate electricity that has low carbon footprint. Life cycle assessment is also important here because it can link the different material energy flows to the service unit provided, but also material flow analysis is key method for this scope.

Supply chains research focuses on quantifying a certain substance emitted in a global supply chain of a certain products, for example greenhouse gases in the supply chain of electric vehicles. This question is studied by looking at the system linkages of global supply chains that connects remote resources uptake and material production to consumption that happens in front of our eyes. The method applied here is life cycle assessment, environmental extended input-output analysis and also combination of so-called hybrid model. When we review the industrial ecology history, and its scopes and methodology, it should be considered as a systematic science. Socioeconomic metabolism a way of framing the system, a scientific principle when to study human and nature interactions from a system perspective.

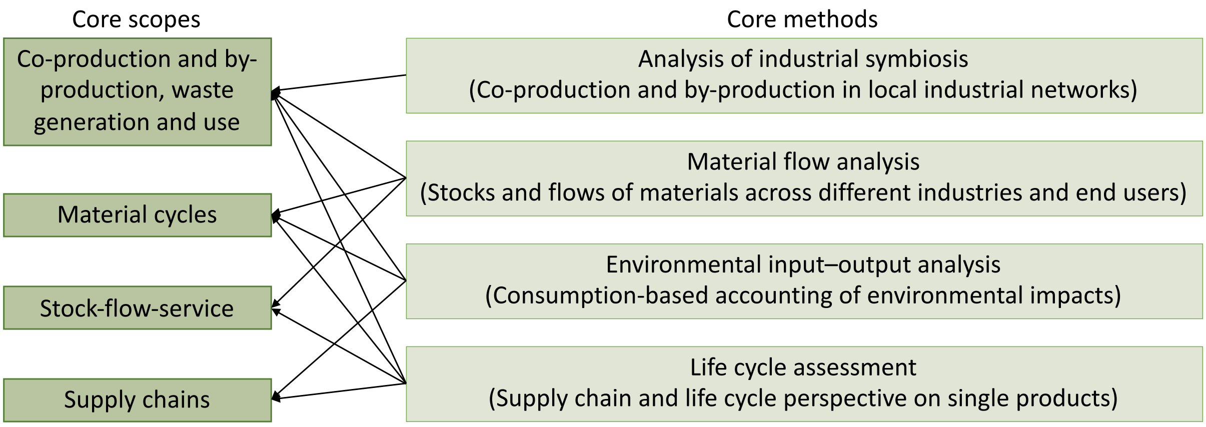


Figure 3 Core scopes studied in industrial ecology

2.1.2 Socio-economic metabolism

Metabolism is a concept adopted from biology, where it refers to the sum of the physical and chemical processes within living beings (Schandl, Müller, and Moriguchi 2015), and first adopted into analysis of material cycles and environmental effects of human activities in 1965 (Beloin-Saint-

Pierre et al. 2017; Wolman 1965). The key innovation of this work analogized cities with ecosystems and analyzing material flows in urban socio-economic systems using ecological principles (Baccini 1997). In the following decades, a substantial number of scholars developed research with the word "metabolism": societal metabolism, urban metabolism, socioeconomic metabolism. We note that each of these three terms evolved separately in parallel to the others, by different people that can meet in the same conference but have very different perspectives, academic backgrounds and research interests: industrial ecology, political economy, social ecology and urban ecology. So, they do have similarities and differences between these researches. For example, in urban metabolism energy flows are very central (Hunt et al. 2014), but not so in socioeconomic metabolism which almost exclusively looks at materials. Another example is that socioeconomic metabolism loves comparing flows to GDP and other macro socioeconomic indicators, and urban metabolism doesn't usually do so – when they try to answer "why do flows happen" they usually look for answers in the urban planning and urban form and urban politics etc. They also focus on different scales and system boundaries – urban metabolism people look at cities and their hinterlands (regardless of whether the hinterland is in the same country as the city), socioeconomic metabolism looks at countries mostly, but also focuses on cities.

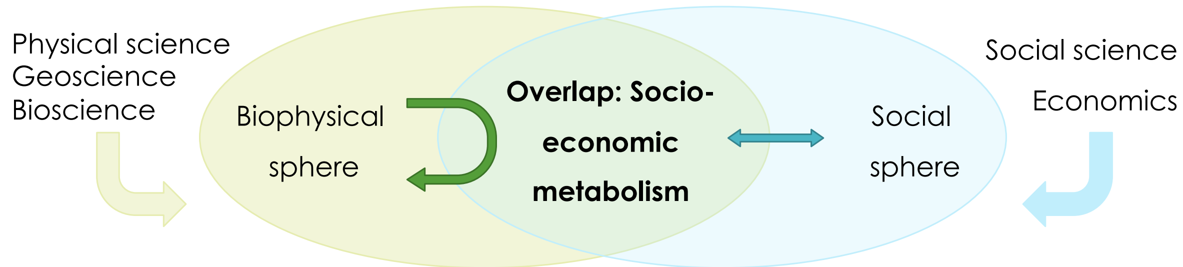


Figure 4 The position of socioeconomic metabolism in the disciplinary

Under the frame of industrial ecology, socio-economic metabolism (SEM) analyzes physical metabolism of resources use, transformation, and discarding and emphasized it is shaped and driven by socioeconomic activities. In light of this, it requires natural science combining with social and economic science (Figure 4). It was originally conducted for the nations, regions and globe for resources conservation and management policy analysis and decision, now increasingly extend to cities as well. Beyond the material cycles and interaction between stock and flows, recent research started investigate the linkages between them and the social service they provided (Carmona et al. 2017). For example, the comparison of materials turnovers and GDP, a proxy for societal wellbeing (Ward et al. 2016), derives as key indicator of resource efficiency for policy making which has been highly concerned (Pacheco-Torgal 2013; Allwood et al. 2013).

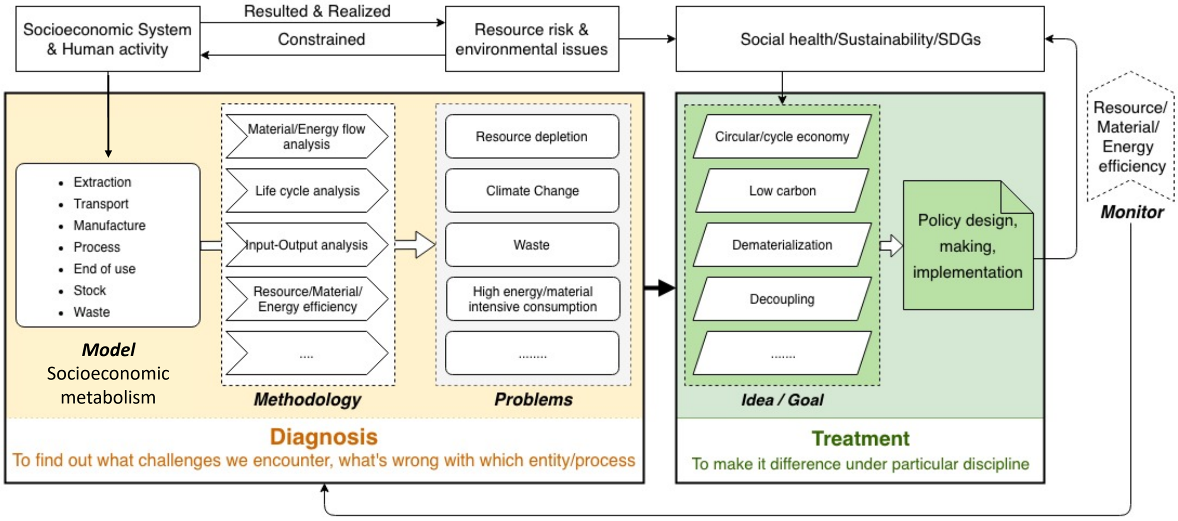


Figure 5 The role of socioeconomic metabolism in sustainability

In order to well understand the connection of socio-economic metabolism and its potential contribution to policy analysis, I summarized the process of addressing environmental issues into diagnosis and treatment (Figure 5). Socio-economic metabolism is the basic model of our society and its involvement, describing resources extraction, transportation and transformation, consumption and use, and discard with major analytical methods of material flow analysis, life cycle analysis, input-output analysis, etc. It finally identifies the environmental impacts by human activities, like resource depletion, climate change, intensive energy/material consumption, etc., and finds out what challenges we are facing now and what's wrong with which entity for process through analysis and understanding the socio-economic metabolism. This diagnosis results will be fundamental when to make reasonable treatments. Correspondingly, the concepts and strategies of circular economy, low carbonization, dematerialization, decoupling, etc., has been proposed as the directions for more detailed standards and regulations toward the sustainable development goals. Moreover, diagnosis process needs to be repeated for monitoring policy effects on tackling the environmental issues. Therefore, socio-economic metabolism analysis is the first step to the final sustainability, hereby, it deserves more attentions and investigations.

2.2 Principles of material flow analysis

Materials flow analysis (MFA) has been one of the main tools to uncover the socio-economic metabolism through systematic assessment of the state and changes of flows and stocks of materials within a predefined spatial and temporal system boundary, further directing toward the management of resource, environment and waste (Brunner and Rechberger 2016). Among the many fields that MFA is widely applied for, a substantial number of researches have been done around metabolism of cities and resource conservation and recovery, especially concerning about material stock accumulation. The basic principle of MFA is mass conservation, namely input to the system equal to the output and net addition within a specific period of time, but to achieve the various research goals, this method gradually develops in different dimensions and models.

Materials. In MFA, material is a very general notion, including chemical substances and compounds, mixtures (e.g. biomass, minerals, fossil fuels, metal materials), components (e.g. batteries of cars and mobile phones, wall and roof of buildings) and goods (e.g. computer). It is noted that energy and related gas emission is usually out of this frame, instead, mostly is the focus of life cycle assessment.

Spatial and temporal boundary. MFA spatial boundary varies from the macro scale, whole world (Krausmann et al. 2017), nations (Gierlinger and Krausmann 2012; Fishman et al. 2014) and regions (Wiedenhofer et al. 2015; Terazono and Moriguchi 2008), to meso scale of cities (Reyna and Chester 2015; Nguyen et al. 2019) and even micro scale of a small piece of area (Tanikawa and Hashimoto 2009), which provides beneficial management implications for decision makers at different administrative levels. Moreover, it is capable to observe the stock and flows status in a particular year, and continuous or discontinuous change of long-term stocks and flows.

Static and dynamic model. Stock and flow estimation of single time point and discontinuous snapshots is usually independent from their past years, so called **static model**. While continuous time series stock and flows analysis could be static or dynamic (stock and flows in present year depend on the past years). Since **dynamic MFA** was first proposed and applied for housing in the Netherlands (B. Müller 2006), inputting the stock data can produce a result of flows (stock-driven model); conversely inputting the inflow data can draw the figure of stock (inflow driven model). The former is also known as demand-driven model that resource requirement and waste generation depend on the population and demand maintaining a certain life quality (B. Müller 2006). It is an effective tool for forecasting stock in use and material flows which are essential for environmental policy making. And it has been put into practice on the stock and flow analysis of residential buildings and household appliances thanks to easy data accessibility at per capita or household level. The latter is capable to yield the outflows and total stock that also can provide retrospective and prospective information of material metabolism.

Retrospective and prospective views. Retrospective research mainly focuses on the metabolism history by tracing back the evolution of materials use and accumulation, informing how it changes and what drives it with the additional quantitative analysis. Prospective research contributes on forecasting future waste generation and resources requirements under different policy or technology scenarios, which is important guideline for strategy decision. Many researches did prospective analysis, followed by retrospective one.

Top-down and bottom-up approach. The distinctness of two approaches lies that bottom-up is dependent on material intensity while top-down not. Figure 6 shows the conceptual flow for top-down and bottom-up approach of construction material consumption/stock, where I depicted buildings in details and other infrastructures in a simple way. **Top-down accounting** utilizes material inflow statistics to determine additions to stock in a series of time periods, referred to as cohorts. Its statistical data usually corresponds to the total consumption, consumption by uses and materials shown in the Figure 6. The material in a cohort gradually depreciates from stock to outflows. By summing the remaining material of all cohorts in a point in time, total MS is obtained (Tanikawa et al. 2015). How detailed the results are quite depends on the available data, for example, the total material stock in buildings could not be disaggregated into material stock by different uses or material types if no corresponding data. Therefore, top-down approach is most applied on the national scale to reveal the general trend of material consumption at macro level, rather than digging into details for different sectors or materials. While the **bottom-up method** starts from the detailed inventory of end-use objects which lists their physical amounts with endogenous attributes. For example, the total floor area of buildings collected from certain local statistical documents may have detailed subdivisions, floor areas by different service types (residential, public or industrial buildings) (Figure 6), by architecture structures (steel frame, reinforced concrete, etc.), by construction periods and by these combinations of attributes. Material intensity coefficients help convert the physical number into the amounts of materials stocked in those end-use objects, and further summed up fot the total amount of materials. If the results of a bottom-up account are "snapshots" of the MS in a single point in time, and owing to its independence from other time frames, this method is "static analysis", but it also could be in dynamic fashion for prospective analysis. Bottom-up method can be further broken down to two subcategories according to the data sources of the inventory: statistical data and geospatial data. Material flow and stock estimations based on various statistical data are carried out by administrative unit, like nations and the whole city. These estimates assist in understanding the accumulation of material over a specific area. However, it is important for sustainable urban planning to know the spatial distribution of MS with its contents using geospatial data. With the help of the Geographical Information System (GIS) platform, each individual of objects and their properties are considered in material stock estimation and depicted in the form of map to show the stock spatial distribution.

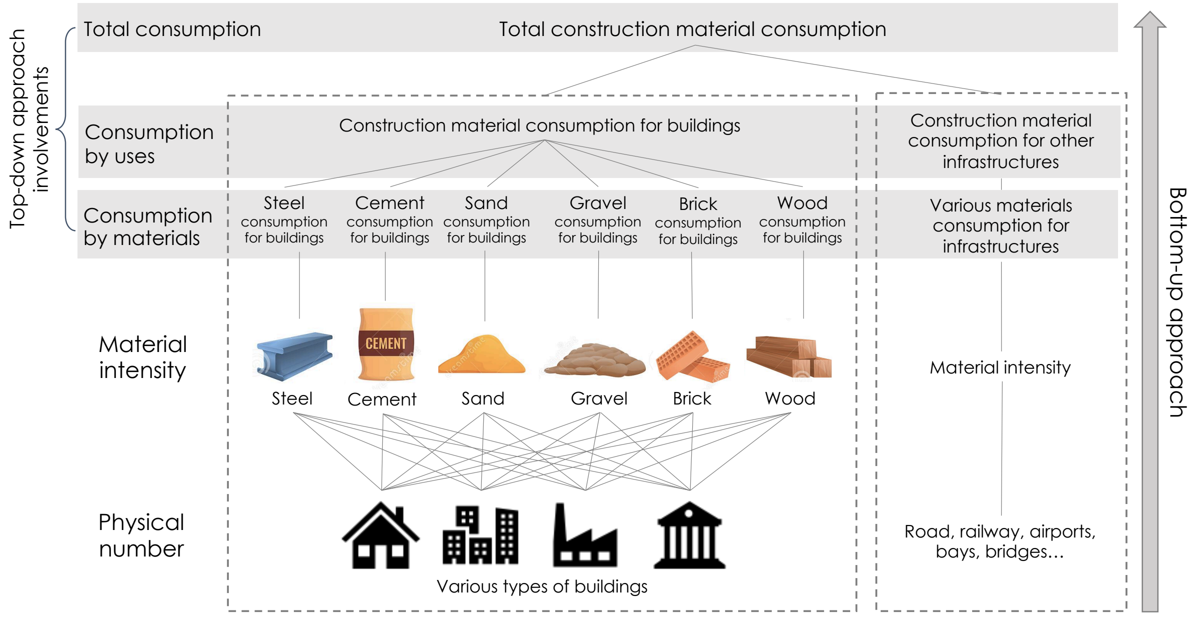


Figure 6 Conceptual figure for top-down and bottom-up approach

Uncertainty. Material flow analysis, or other methods in industrial ecology, has inherent uncertainty due to models setting and parameters assumptions in the model (Laner, Rechberger, and Astrup 2014), which hindered us to capture the real values. This is tricky to improve or resolve - we can never generally compare which model or parameter fits better to reality. What we can do is to build up model and set parameters based on fully understanding of research case, moreover, uncertainty analysis is required to give a confidential interval of results instead of exact figures.

2.3 State of the art

Top-down approach is not suitable for this study focusing the construction materials stocked in the building system of China, because there is no more detailed subdivisions of construction materials for buildings use or infrastructure use. Bottom-up method provides the possibility with available data. This part will review the literature around the bottom-up methodology, including analysis of long-term evolution of material stock and flows and spatially explicit material stock accounting. These two subsections will summarize the researches about material stock and flows with statistical data and GIS data respectively. Although they are divided into two parts based on data source and methods, here I will not introduce much methods and compare the detailed parameters they used, which will be elaborate in the next chapter. Instead, Research scope, purpose, findings and limitation will be described. Finally state of the art is closed with research of building-related materials metabolism in Chinese cases.

2.3.1 Spatially explicit material stock accounting

The lack of temporal-spatial view on the urban scale can be found when we traced back the literature on urban metabolism. The conventional economy-wide material flow analysis is helpful to reveal the evolution of input, output and stock within the city, to diagnose which part is unsustainable, and to examine the linkage with the socioeconomic growth. It is indeed an effective tool to understand the urban metabolism and its environmental impact from the view of "outside" of the objective boundary, yet the inside is a black box (Beloin-Saint-Pierre et al. 2017). To unpack it, a considerable amount of research has been carried out as combinations of various of dimensions, which are the materials transaction or transformation (Liang and Zhang 2012), components providing fundamental service for human and economic activities, like buildings, road system, sanitary system, etc. (e.g. (Arora et al. 2019)), and the objective product, material or substance. However, the element of space in the black box of city did not get much attention (Pistoni and Bonin 2017). Since the informative spatial distribution of material stock has been estimated based on high resolution GIS data with the geo-localization of buildings and other infrastructures, the significance of spatial view on material stock analysis has been well recognized. GIS is quite helpful to answer three questions: (1) how many material stock (urban mines) are present, (2) where they are located, and (3) how much demolition waste would be generated and what the component is (Cousins and Newell 2015; Li and Kwan 2018). Answers of the first two questions are the prerequisite to address the third one.

(1) Present status of material stock

Regarding the first two questions, a few of paper has made effort on material stock estimation with resolution refined GIS data to reveal the spatial distribution of material stock and potential demolition waste. For example, Kleemann et al. (2016) investigated the metallic, mineral and organic resources stocked in building sector of Vienna of the year 2013, and arrived at the results of 380 Mt in total for the whole city and 210 t at per capita level. Similar research on residential buildings was conducted for a Latin-American city of Chiclayo in Peru (55.71 km^2), total material stock of nine kinds of primary construction material was estimated as 24.4 Mt and 47 t per capita in 2007 (Mesta, Kahhat, and Santa-Cruz 2019). In addition to buildings, GIS data has been also applied in material stock estimation of infrastructure sector, especially transportation network. With the detailed GIS urban roads data of Beijing, Guo et al. (2014) argued that the total stocks can be disassembled into a number of stock parts rather than obtained by statistical estimation, facilitating inner structure understanding. Footways, cycleways, tramlines, railways, etc. were included in the system boundary in case of four cities in Sweden with the help of OpenStreetMap ArcMap extension tool (Cruz 2016). Undoubtedly, the spatial and temporal extent of these research largely depends on the availability of GIS data. Therefore, the spatial extent is small (even if administrative boundaries can be broken) in GIS-based research. With the emergence of some commercial map companies, large-scale GIS inventory material stock evaluation becomes possible.

The material stock estimation was done for buildings and roads of the whole Japan, finding that roughly 80% of the material is condensed in major urban conglomerations—approximately 20% of Japan's area (Tanikawa et al. 2015).

The significance of GIS-based material stock accounting was extended in addressing practical matter, like informing disaster risk planning. An estimation of the scale of lost buildings and infrastructures' material stock would be the basis of the amount of materials necessary for future reconstruction as well as the subsequent waste flow generation, more importantly, proper policies could be proposed for the recovery of stricken areas, which was emphasized in the estimation of material stock lost in the Great East Japan Earthquake (Hirakawa et al. 2011). Global issue-extreme weather events and sea-level rise due to climate change will challenge the resilience of material stock and put total 11.9 Mt MS of buildings into high risk, for the main island of the Grenada (Symmes 2018).

(2) Material stock and flows over space and time

Above GIS-based research only accounted the material stock in a certain year, so called snapshot, which is a good way to capture the current MS status of quantity and spatial distribution, but does not enable to know the changes of stock and flow due to lack of time series. A number of papers have devoted on filling in this gap. For instance, J. Han et al. (2018) presented the spatiotemporal patterns of the material stocks of infrastructure with six grid-level snapshots from 1980 to 2010 for the case of Shanghai, China, and estimated the material flows with assumption of lifetime function as applied in dynamic model. This helps to investigate the metabolism rate, however, did not answer the question (3). Various attempts have been done for it. Wu et al. quantified the material stock of the present year in GIS , but considered it as future demolition waste by setting demolition time of buildings, which year needs to deal with how much demolition waste was evaluated with taking account recycling and landfill (Wu, Wang, et al. 2016). Heeren and Hellweg used a probabilistic modeling approach to calculate future material flows for the individual buildings under six scenarios (Heeren and Hellweg 2019).

Another important approach is 4d-GIS, adding time dimension to 3d-GIS, proposed to depict spatiotemporal patterns of material stock and flows by Tanikwa et al. in an application of Salford Quays in Manchester (approximately 8.0 km^2) over time from 1849 to 2004 (nine snapshots) and Wakayama City centre, Japan (11.3 km^2) during 1855-2004 (eight snapshots) (Tanikawa and Hashimoto 2009). Another great contribution of this study is to provide an alternative method of estimating building lifetime, which is a key indicator of metabolism and parameter in dynamic model, which largely promotes the possibility to estimate the future waste by combining results for the total material stock and the expected building lifespan. Miatto et al. applied this methodological frame and predicted waste flows will increase to 1.9 tonnes per capita in 2030 in Padua, Italy, from almost one tons per capita in 2007 (Miatto et al. 2019). The same model used for Longwu Village in Shenzhen city expected 125 Kt C&D waste from 2006 to 2022 (H. Wang et al. 2019). Sugimoto et al. predicted the building material flows for two scenarios up to 2050 supporting the future policymaking (Sugimoto, Morita, and Tanikawa 2015). In regions or cases where geospatial data is sufficient developed since early decades, the spatiotemporal changes in material stocks and flows can help to more fully understand the characteristics of urban metabolism and identify problems that hinder sustainable development.

2.3.2 The evolution of material stock and flows

The evolution of material stock and flows and their forecasting have been positioning the center of SEM research at multiple scales as it provides the fundamental and important information for policy decision and city management. Among the paper reviewed here (Table 1), end-use objects are residential/non-residential buildings, other infrastructures, electrical appliances, electronic equipment, etc. Buildings, especially residential buildings are a major concern in research of construction materials stock and flows. Corresponding materials are those primarily embedded in end-use objectives or some specific metals or chemical compounds. Their study boundary is usually for nation or big cities, and tends to have long time series of both retrospective and prospective investigation. In case of prospective research, several scenarios were set with different population growth rate, service demand, and policy interventions, for further helping the policy making. With regard the method, dynamic material flow analysis was proposed to overcome the data insufficiency. Most of research applied stock-driven model, so-called demand-driven model, owing to easy access to the data and close link to the human needs. To this date it's stuck in residential building analysis, and did not take sufficient account of non-residential buildings and infrastructures (Augiseau and Barles 2017). But non-residential buildings are much more diverse in function, components and their respective materials (Schebek et al. 2017), which also calls for more examinations. A considerable number of studies employed inflow-driven as well with stock-driven approach. Applications of these dynamic methods relied on the several assumption and parameters determination, which are usually discussed as uncertainty analysis in the paper. More details about method in Table 1 will be further elaborated in section 3.3.

Table 1 Dynamic material stock and flows research

Paper	End-use object	System boundary		Materials	Specific model	Initial condition	Lifetime distribution	Parameter assumption
		Spatial	Temporal					
(Bader et al. 2011)	buildings, infrastructure and mobiles	Switzerland	1840-2060	Copper	Stock-driven	NA	two-parameter Gauss function	40(10)
(Bergsdal et al. 2007)	Residential buildings	Norway	1900-2100	Concrete and wood	Stock-driven & inflow-driven	NA	Normal distribution	3 scenarios
(T. Wang et al. 2015)	Whole buildings	China	1900-2050 (showed results from 1950-)	Steel	Stock-driven & inflow-driven	Initial stock/life span	Weibull distribution	Varies with different categories
(M. Hu, Pauliuk, et al. 2010)	Residential building	China	1900-2100	Iron and steel	See above	NA	Normal distribution	Varies along the time
(Cao et al. 2018)	Urban housing	China	1985-2100	9 kinds of construction materials	Stock-driven	NA	Weibull distribution	Stochastic (bootstrap method)
(Sartori, Sandberg, and Brattebø 2016)	Residential building	Norway	1800-2100 (1900–2050 is of highest interest)	-	Stock-driven	Initial demolition	Weibull distribution	125 years for average lifespan
(Džubur and Laner 2018)	Building	Vienna	1950-2100	Wood and contaminants	Leaching & delay model (inflow-driven)	Split to age categories	Weibull distribution	Varies with wood products in buildings

(Wiedenhofer et al. 2015)	Residential buildings, roads, and railways	EU25	2004-2009,2020	nonmetallic minerals	Bottom-up Leaching model	Not necessary	Demolition rate and replacement rate	-
(Shi et al. 2012)	Building, road and railway	China	1950-2050	Cement and steel	Stock-driven model	NA	Normal distribution	Varies with types
(Sandberg et al. 2016)	Dwellings	11 European countries	1900-2050 (input parameters from 1800)	-	Stock-driven model	Initial demolition (SI)	Weibull distribution for lifetime	Varies with countries
(Bergsdal et al. 2007)	Dwelling stock	Norway	1900-2100	-	Stock-driven model	NA	Normal distribution	Varies with scenarios
(M. Hu, van der Voet, and Huppes 2010)	urban housing system	Beijing	1949-2050	6 kinds of construction materials	Stock-driven & inflow-driven	NA	Normal distribution	25(5) 50(10)
(L. Zhang, Yuan, and Bi 2011)	5 kinds of household appliances	Nanjing, China	2009-2050	-	Stock-driven	Initial year determined	Weibull distribution with 3 parameters	Fitting for different products
(Hong et al. 2016)	Residential & commercial building	China	2010-2050	4 kinds of construction materials	Stock-driven	NA	Normal distribution	30–40 years for urban buildings and 15 years for rural
(Bergsdal, Brattebø, and Müller 2014)	Buildings	Norway	1950-2100	polychlorinated biphenyls (PCBs)	Stock-driven model	NA	Normal distribution	Varies with applications and use

2.3.3 Buildings material metabolism in Chinese cases

This part mainly reviews what's research about construction material stock and flows going on in Chinese cases. Three major topics can be summarized and they are conformed in international studies. (1) Retrospective and prospective material stock and flows were the basic step for further study and strategy guidance: to identify the characteristics of the material stock and flows evolution and to define future recycling potential or waste rick under different scenarios. (2) Some research linked material stock and flows to energy consumption and other environmental impacts: to evaluate energy consumption during the whole life cycle of construction material metabolism combined with LCA and to explore the possibility of climate change mitigation in process of metabolism. (3) Socio-economic drivers: to examine the socioeconomic factors that drives constant increasing of construction stock and to unpack the influence mechanism so that potential solution could be found for sustainable material consumption and accumulation.

Figure 7 presents the most of study was conducted at national level, followed by city level which, however, preferred municipalities like Shanghai or Beijing (M. Hu, van der Voet, and Huppes 2010; D. Hu et al. 2010; C. Huang, Han, and Chen 2017). The country-level study tends to have longer time extent as well, spanning last and present centuries (M. Hu, Pauliuk, et al. 2010; M. Hu, Bergsdal, et al. 2010). Provincial and urban studies have shorter temporal extent, possibly due to harder access to data. In Figure 8, The research objects are mainly concentrated on buildings (T. Wang et al. 2015; T. Huang et al. 2013), divided into urban residential buildings, urban non-residential buildings and rural buildings (Cao et al. 2018), and a few of research on transportation networks and other municipal infrastructure (Wen and Li 2010; Hou, Tian, and Tanikawa 2015). The top five primary materials of interest in the study are steel, cement, brick, sand and gravel among the selected literature.

What methodology employed depends on the research scale. Almost all selected papers used bottom-up method, namely material intensity dependent method. Thirteen of them applied stock-driven dynamic MFA which has been widely applied in Chinese cases since it was proposed by Müller in 2006 (D. B. Müller 2006). And anther eleven cases analyzed material stock by static accounting, including GIS-based way. For single or several separate built works, construction material metabolism estimation is usually derived from construction blueprints more accurately.

Material intensity varies with structure, construction year, functional type, etc., even case by case, and it is thus hard to determine. Compared with Japan, UK, Sweden, and Netherlands, where MI databases of residential buildings have been compiled (Gontia et al. 2018; Tanikawa and Hashimoto 2009; D. B. Müller 2006), there are currently not many ready-available MIs in China. A valid set of MIs can be sourced from the Construction Project Investment Estimation

Handbook (Yu and Li 1999), which reports the MIs for buildings by structure, use type, and cohort, and it has become the reference manual for Chinese MIs. Yet this is not the only source of MIs, and over the years, researchers have engaged in the calculation of specific MIs for China. Shi and Huang and their colleagues reported a set of MI parameters for the whole country (Shi et al. 2012; T. Huang et al. 2013); Cao et al. assigned MI parameters through bootstrap and Monte Carlo simulation basing their analysis on the information sourced from Yu and Li (Cao et al. 2018; Yu and Li 1999). Some others conducted a survey and estimated for a specific study area: Liu and Hu sampled 100 Beijing residential buildings of different structures and estimated the MI of six materials (cement, gravel, sand, steel, timber, and bricks) (Liu and Hu 2006). The China Architecture Design & Research Group investigated 226 buildings (residential and public) across the country and estimated the average content of steel, cement, concrete and walling materials per unit of construction area (L. Gu 2009). The construction material stock/flow is quite sensitive with MI; however, the uncertainty still keeps it mystery.

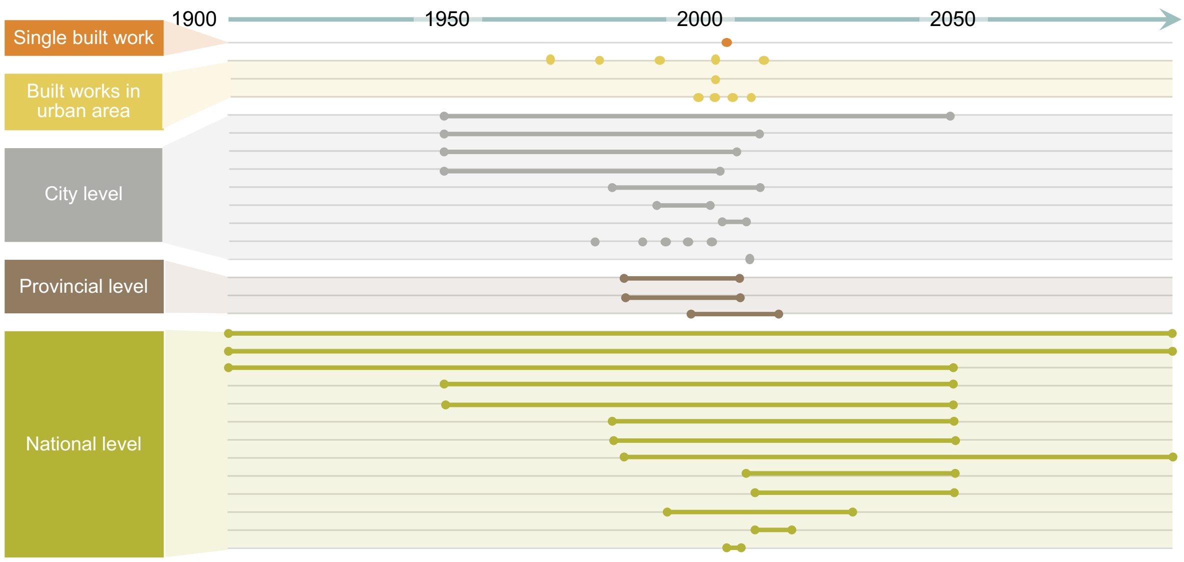


Figure 7 Spatial scale and time extent of selected papers of construction material metabolism in Chinese cases

Lifetime function and parameters. Most cases employed Normal distribution for simplification because the average lifetime is one of its parameters. Average lifetime is the most crucial to determine the demolition curve and further the potential waste. Basically, present publications/experts suggest lifetime of urban building as 30-40 years, rural building as around 20 years based on their own experience, although it varies a lot case by case. Weibull distribution got more applications to improve the reliability of models. Figure 9 presents the citation relationships for material intensity and lifetime parameters respectively, where these two key parameters in bottom-up method and dynamic manner are very dependent on a few of core papers. Such fundamental parameters require more concern.

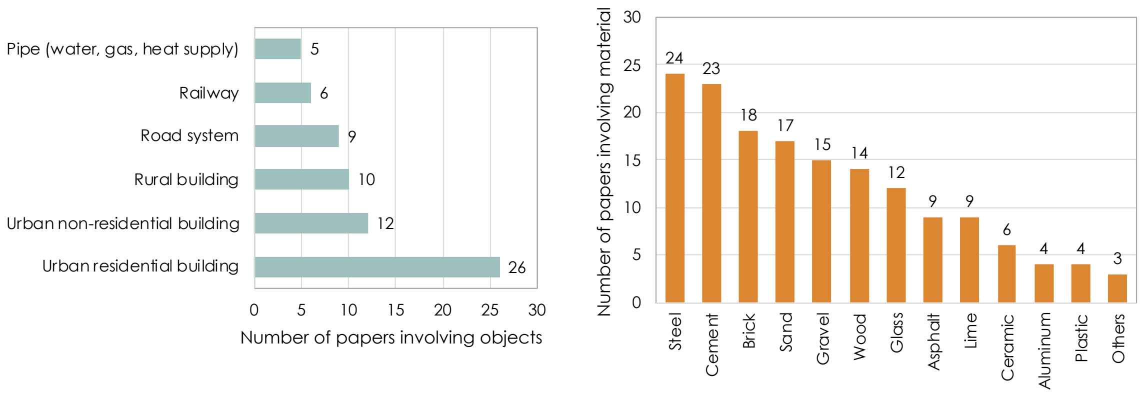


Figure 8 End-use built objects and construction materials

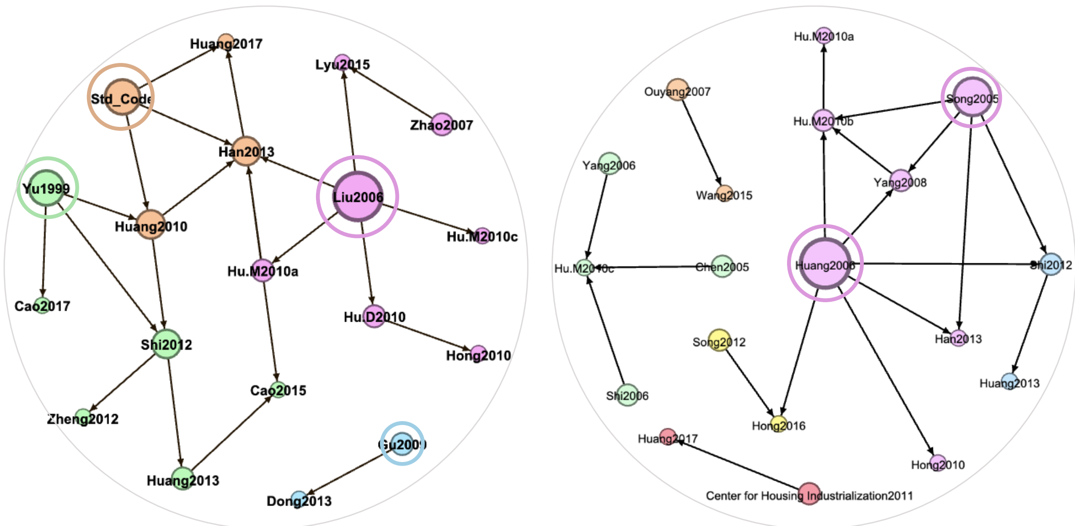


Figure 9 Bibliometrics over the body of selected literature (Left: material intensity; Right: lifetime function and parameter)

"Easily-done" work has been studied in past ten years. Available data is the footstone of research skyscraper; however, it is risky to produce papers with similar topic in similar way. Overview at construction material metabolism of China shows that construction material metabolism is often investigated along with, or even for conducting energy flow analysis. Increasing amount of materials have been stocked and this trend would continue in the context of fast-paced urbanization. But the effect of urbanization on building material accumulation has not been well figured out. Basically, it is urgent to establish systematic material intensity database for Chinese buildings and look for more scientific tools to understand the building lifetime for dynamic MFA. Downscaling to city level MFA (except for Beijing, Shanghai, Tianjin these provincial-level mega cities) are also required because city consumes and stocks most part of resources and materials.

3. Bottom-up methodology

3.1 General modeling

Bottom-up method starts from the detailed inventory of end-use objects which lists their physical amounts with endogenous attributes. For example, the total floor area of buildings collected from certain local statistical documents may have detailed subdivisions, floor areas by different service types (residential, public or industrial buildings), by architecture structures (steel frame, reinforced concrete, etc.), by construction periods and by these combinations of attributes. Construction materials stocked in each sub-category in year *t*, therefore, can be derived by timing corresponding material intensity with the following function:

$$MS_{a,t} = N_{a,t} \times MI_a \qquad \textit{Equation 1}$$

Where *a* generally denotes the index of a certain attribute of the end-use object, we can add more index here to refer multiple attributes depending on how detailed the data is and research objects. *MS* is the material stock, *N* is the physical number of objects, and *MI* is material intensity- the amount of material required in per physical unit of end-use objects - which will be elaborated in following subsection 3.3. Substitution *MS* and *N* with material inflow and corresponding physical amount of new input of end-use objects in year *t* will easily yield the material mass entering into stock at the time of *t*.

Among the research of bottom-up method, some only focuses on material stock and aims to uncover how huge amount of material accumulation in the past and at present, also called as material stock analysis (MSA). It estimates the material stock directly with physical stock data of each year or several specific years, that is static model. However, when we talk about metabolism and its characteristics, it should be a circle of materials from flowing into stock and finally getting out from stock as wastes in a period of time later, even reentering the next cycle by sound recycling. If sufficient data is accessible, for example, in case of all physical stock, input and output are well recorded, static manner can be simply used for accurate estimation of material stock and flows. However, data always impedes this way. Therefore, dynamic model with lifetime function (Figure 10) was proposed to model the reality and provide rough estimations to understand metabolic flows for resource conservation and management.

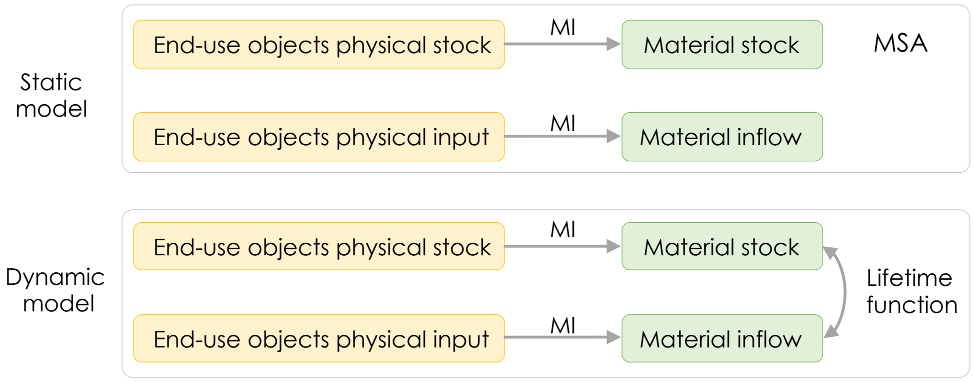


Figure 10 Static model and dynamic model of bottom-up method

3.2 Static manner

Static manner follows the *Equation 1* with various data of end-use objects and corresponding MI. Because data structure varies, for example, statistical data includes information of how much floor areas for each service type while GIS data usually has attribute of building height, attribute index in above equation is also different, which will be elaborated in following sections separately.

Using statistical data of physical stock for years is a static, and quick way to estimate the material stock. Its merit lies on high possibility to compile a large spatial scale and long temporal series of data, which further benefits to capture the characteristics of regional variance and evolution of material stock. While shortcoming lies on its administrative-unit-based statistical way, thus we could never know what is the case inside of these unit- spatially black box. Therefore, GIS data was introduced to fill in this gap. GIS database for buildings provides a more detailed inventory including every single building and its several attributes, of course geographical location as well. ArcMap platform is able to obtain the area of each footprint, then total floor area would be addressed out by timing with the number of floors. The following steps for final material stock estimation are almost same as described above. The strength of GIS data is explicitly presenting the spatial distribution of material stock and breaking down the restriction of administrative boundaries. Its weakness is also apparent. GIS data of buildings originally contains the location and shape information, other attributes we need for material stock estimation are required much work to collect and compile. Therefore, it is rare to have GIS based MSA of long continuous time series, instead, it is common to select specific years as snapshots from history of material stock.
It is worth noting that in an ideal situation where all the data can be obtained, then static manner would be the first option to accurately calculate the material stock and flows. But there is little available data in reality, therefore dynamic models are required to make estimations.

3.3 Dynamic manner

3.3.1 Dynamic MFA generalization and interpretation

(1) Dynamic model generalization

To generalize the model of dynamic MFA, it is necessary to introduce the convolution firstly. Convolution is a mathematical operator between two functions *f* and *g*, denoted as $f * g$, that expresses how the shape of one is modified by the other (Sartori, Sandberg, and Brattebø 2016). The convolution between *f* and *g* in the discrete and continuous form is written as *Equation 2* and *Equation 3* respectively. They have a feature in common that index of result n is equal to sum of index of *f* and *g* on the right side, i.e. $n = \tau + (n - \tau)$. Convolution has been widely applied in various domains (like engineering, physics), dynamic MFA is one example from the field of IE.

$$(f * g)(n) = \sum_{-\infty}^{\infty} f(\tau) g(n - \tau) \qquad \textit{Equation 2}$$

$$(f * g)(n) = \int_{-\infty}^{\infty} f(\tau) g(n - \tau) d\tau \qquad \textit{Equation 3}$$

(2) Two ways of model expression

It is typical in the dynamic MFA literature to assume a certain lifetime function for reflecting the relation between the outflow and inflow (Nakamura and Kondo 2018), and probability distribution function is the most case. Probability distribution function usually applied, like Normal, Weibull, Gamma and Lognormal, is all continues (discrete function will be discussed in later section), while the available data in relevant research is year-based in the discrete form. Thus, there are two ways of expressing the dynamic MFA model. The first way is PDF (probability density function)-based (*Equation 4* and *Equation 5*), where outflow is the convolution between the inflow and PDF of discard (obsolescence or demolition, denoted as small d instead of D) as shown in *Equation 4*. Then mass balance equation between stock, inflow and outflow will result in stock or inflow (*Equation 5*), where *S*, *I*, *O* simply refer to the stock, inflow and outflow of goods, materials or substances with the unit of the number, size (area, volume) or mass, *c* refers to the certain year between the beginning year t_0 and the estimated year *t*. I_c refers to the inflow entered in the year c.

The second way is CDF (cumulative distribution function)-based (*Equation 6* and *Equation 7*), in which stock is the convolution of the inflow and CDF of remaining (or survival, denoted as capital R in *Equation 6*), that means the stock at time *t* is the accumulation of the all remaining inflows from the far beginning. And outflow can be derived from the mass balance equation sequentially (*Equation 7*). The results calculated by these two ways will be slightly different because sum of several discrete values of PDF cannot reach the corresponding CDF, $\sum d \neq D$. Most literature to the date set the model in PDF-based way (Sartori, Sandberg, and Brattebø 2016; M. Hu, van der Voet, and Huppes 2010; Bergsdal et al. 2007; Krausmann et al. 2017), while quite few study modeled the dynamic MFA in CDF-based way (Fishman et al. 2014). It is acceptable to model in either way, however, we recommend to use CDF-based one because the PDF value is the slope of CDF, an instantaneous value not suitable for year-based research. PDF-based model can be modified to CDF-based (*Equation 8*), that is employed in handful literature (Cao et al. 2018; Daigo et al. 2007).

$$O_t = \sum_{c=t_0}^{t} I_c \times d(t-c) \qquad \textit{Equation 4}$$

$$S_t = S_{t-1} + I_t - O_t \qquad \textit{Equation 5}$$

$$S_t = \sum_{c=t_0}^{t} I_c \times R(t-c) \qquad \textit{Equation 6}$$

$$O_t = S_{t-1} + I_t - S_t \qquad \textit{Equation 7}$$

$$O_t = \sum_{c=t_0}^{t} I_c \times [D(t-c) - D(t-c-1)] \qquad \textit{Equation 8}$$

(3) Insight into stock- and inflow- driven model

If the lifetime function is determined, inputting the stock data can produce a result of flows (stock-driven model); conversely inputting the inflow data can draw the figure of stock (inflow driven model). The former is also known as demand-driven model that resource requirement and waste generation depend on the population and demand maintaining a certain life quality (B. Müller 2006). It is an effective tool for forecasting stock in use and material flows which are essential for environmental policy making. And it has been put into practice on the stock and flow analysis of residential buildings and household appliances thanks to easy data accessibility at per capita or household level. The latter is capable to yield the outflows and total stock that also can provide retrospective and prospective information of material metabolism.

However, the distinction between these two models does not only lie in the input data in hand, and also what results represent in practical, which is vital to understand and interpret results especially when linking to policy implications but has not been discussed yet. It is noticed that "in-use" is added in front of stock for emphasizing its status of being used in stock-driven research, while inflow-driven applications do not. This arises the discussion of classification of stock and related span. Tanikawa et al. (2017) and Murakami et al. (2010) have elaborated the stock classification and various "life" terminologies in their work respectively, we followed and combined their basic structure with some little modification in Figure 11, where most terms can be found in above papers. Rather, the finished durable products and constructions (*P*) going to the market ready for distribution or transaction are then sold, possessed and put into use by consumers (*C*), as a new layer of in-use stock (S_2) in a given period of time (usually one year in IE), the leftover part halt in the market for the next period are first time named as in-market stock (S_1). After a certain period, in-use stock becomes obsolescence that can never be used any more but still remain where they had been used (obsolete stock, S_3), or waste through discarding or demolishing activities (D_1). This process involves two important spans for dynamic MFA: service lifespan and duration in use, both of which can be applied for achieving specific research purpose.

What really matters is if input information matches the lifespan. In inflow-driven model, for example, if input is the production or construction and we use service lifespan as the lifetime in *Equation 6*, the estimation of stock includes in-use stock and in-market stock (Figure 11). Likewise, if we input consumption and duration in use as lifetime, the estimated stock of model represents in-use stock exclusively. Inversely, in-use stock is usually as input of stock-driven model with duration in use as lifetime, the estimation of inflow is consumption rather than production/construction. Therefore, inflow-driven model can result in different stocks and outflows with various lifespan. While stock-driven model is often constrained in the in-use stock and corresponding inflow of consumption. There is gap between consumption and production, calling attention for policy makers to consider in-market stock when to plan future productions or constructions.

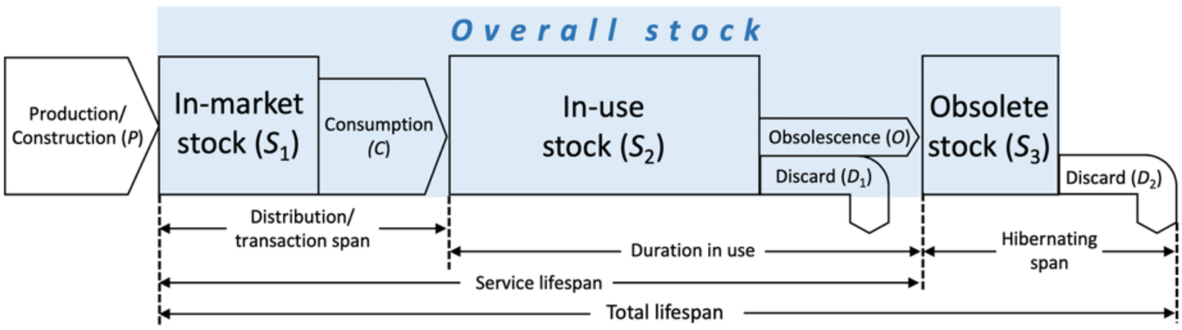


Figure 11 Schematic diagram of stock, flows and lifespans for commercial durables and constructions.

(4) Simplifications and assumptions

The model trying to simplify the reality and describe the future development has uncertainty in the inputs (Sandberg, Sartori, and Brattebø 2014). Besides the variation and reliability of time series input data, the model setting makes it inherently uncertain in dynamic MFA model (Laner, Rechberger, and Astrup 2014), including lifetime function and initial condition. The uncertainty derived from the diverse assumptions for lifetime function in the model has been much discussed and understood in terms of product lifetime function selection and its parameters. For instance, building demolition pattern has been tested with five commonly used distributions to empirical data from 4d-GIS cases and proved that that right skewed distributions performed very well (Miatto, Schandl, and Tanikawa 2017). However, lifetime function and its parameters vary with products or one product with various features, different historical periods and spatial geographical areas. Although they can be determined by employing parametric approach or non-parametric approach (Oguchi et al. 2010), substantial empirical information is required but not easy to obtain. Accordingly many scholars simplify the dynamic MFA model by assuming Normal distribution with parameters of average lifetime and standard deviation, or Weibull distribution with shape and scale parameters which can be referred from the past empirical data, knowledge or experts (Krausmann et al. 2017). Yet it is acknowledged that an accurate lifetime function estimation will never be captured.

Nevertheless, assumption of the initial condition is rarely discussed and even entirely neglected sometimes. To trace back to the real initial year ($Stock_0 = Inflow_0 = Outflow_0 = 0$) is easy for new high-technology electronic products, like computer, smart phone or new energy vehicles, but impossible for durables that has existed for centuries from far history ago, like buildings. In thus cases, initial year is usually determined by the available data in practice, especially in buildings related research which I am going to discuss around in the following. A complete overview of stock and flow for the initial year is necessary which is also quite challenging (Brunner and Rechberger 2016; Vellinga, Berkhout, and Gupta 1998). In the modeling metal stocks and flows, the initial condition of the model depends primarily on the temporal extent chosen: "if analyses go far back in time, initial stocks and flows are often considered zero at t = t_0. If the temporal extent is short or starts in the present, initial stocks, and flows are defined based on available data or the authors' assumptions" (E. Müller et al. 2014). The long time period is important since copper has long residence times of up to 50 years(Bader et al. 2011).But in the buildings dynamic MFA literature reviewed in section 2.3.2, the treatment of initial conditions can be roughly divided into three categories (detailed reference listed in Table 1.

(1) It is not mentioned clearly in the article, but initial condition assumption can be inferred as $Stock_0 = Inflow_0$ from the result outflow starting from zero (M. Hu, Pauliuk, et al. 2010; Cao et al. 2018; Shi et al. 2012).

(2) Although it is not mentioned in the text, the earlier period is used as the buffer time, and only the subsequent results are explained to avoid the impact of the initial condition on the initial results. For example, all inputs with a time horizon from 1800 to 2100 were used for the case study of Norwegian residential building stock although the period 1900–2100 is only presented when interpreting the results (Bergsdal et al. 2007). Some other cases also employed this approach (T.

Wang et al. 2015; Sartori, Sandberg, and Brattebø 2016; Sandberg et al. 2016). Particularly, Krausman et al implemented "spin-up period" which is determined by the longest lifetime used in the modeling (80 years) and begins in 1820, to provide an appropriate initial value of material stock in 1900 (Krausmann et al. 2017). Similarly, Fishman et al. set the first decades of the series as a "buffer" to make material stocked during that period negligible (Fishman et al. 2014). All of above literature seems to acknowledge dynamic MFA is appropriate in long-term analysis with a necessary prepared period where the results are considered as greatly biased. However, how long the temporal extent should be for guaranteeing the dynamic MFA effectiveness is not clear yet.

(3) The initial stock is split into several cohorts based on the available information, rather than arbitrary assumptions, to improve the reliability of the model results.

Dynamic MFA calculates the stock by aggregating the remaining inflows after the part of them is discarded from the system with different delayed rates for different building cohorts. Because of this seemingly reasonable theoretical framework, it has been widely used for retrospective and prospective material stock and flow estimation for various materials and products in the industrial ecology domain. However, how much can dynamic MFA-based estimation reflect or capture the reality has not been discussed under the limitation of observable data? And the impact of initial condition is often ignored in its application. The above empirical results raise the questions to dynamic MFA practice in the building stock estimation.

3.3.2 Impact of initial condition

(1) Theory

Here dynamic MFA is assumed as the perfect model of reality, which is a strong assumption. To more generally observe the impact of the initial condition, we proceed in three steps. First step for the original estimation: assuming information can be traced back from the very beginning, the relation of stock and inflow in a certain year *m* and *m+n* (m>0, n>0) can be presented in *Equation 9* and *Equation 10* respectively:

$$S_m = \sum_{c=0}^{m} I_c \times R(m-c) \qquad \textit{Equation 9}$$

$$S_{m+n} = \sum_{c=0}^{m+n} I_c \times R(m+n-c) \qquad \textit{Equation 10}$$

Second step for the estimation from the base year *m*, namely the stock of year *m* is the initial stock: the Equation 10 can be rewritten in the following with the simple assumption of $In'_0 = S_m$:

$$S'_{m+n} = \sum_{c=0}^{n} I'_c \times R(n-c) \qquad \textit{Equation 11}$$

where $I_0' = S_m$, the inflows for the following years I_c' are the same as $I_{m+c}, c \in [1, n]$. S_{m+n}' refers to the estimated stock in year *m*+*n* with initial stock S_m. Here *n* is the temporal extent of research, depending on the research objective and data availability. One implicit assumption in the formula *Equation 9* to *Equation 11* is the delayed pattern following the identical probability function for the all historical inflows. Finally, the third step is to calculate the error:

$$Error = (S_{m+n}' - S_{m+n})/S_{m+n}$$
$$= [S_m \times R(n) - \sum_{c=0}^{m} In_c \times R(m+n-i)]/S_{m+n} \qquad \textit{Equation 12}$$

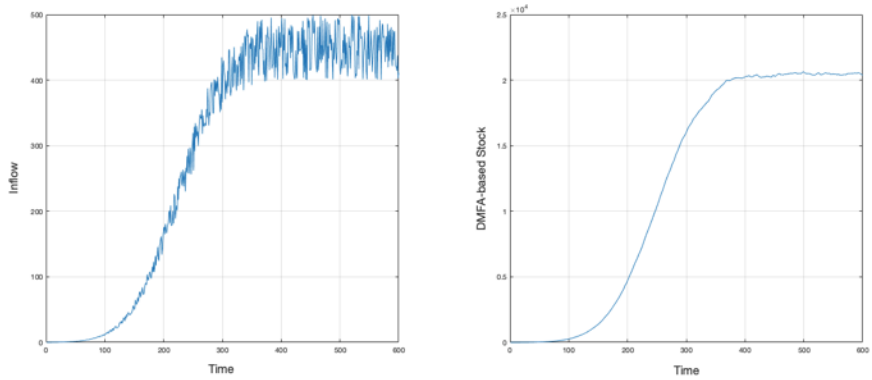
If delayed function R is the geometric distribution, $S_{m+n} = S_{m+n}'$ will be derived, reflecting PIM is not influenced by the initial year. While in case of dynamic MFA, it is hard to tell the error negative or positive as it is subject to many determinants, how much inflows are before and after the year *m*, the research period *n*, delayed function and corresponding parameters. Various possible combinations of them will yield to different results. Even though we can simply infer that error can be acceptable when a smaller stock in the base year combines a great accumulation after year m, namely a smaller m and longer research period n, it is impossible to conclude the exact threshold values for them. Simulation perhaps can provide some hints.

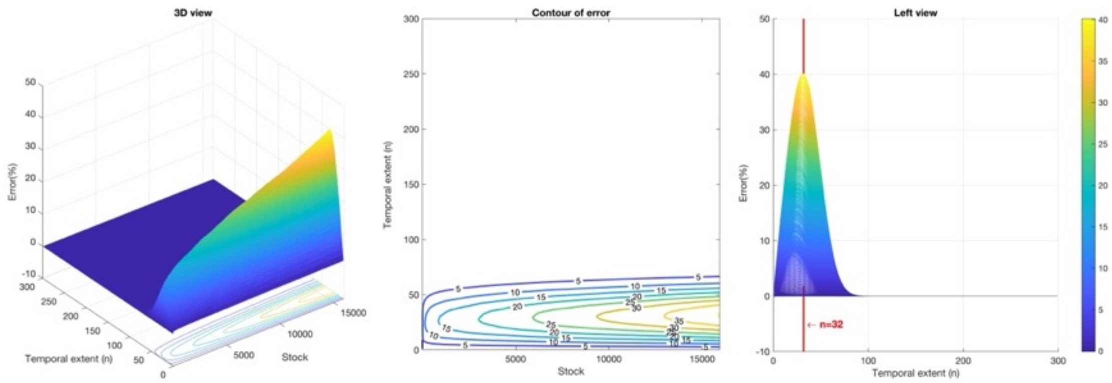
(2) Simulation

With the simulation, I would like to try to answer the questions: how initial year *m* and research period *n* impact on the final results? How long should the research period *n* be determined when the error of results is acceptable? Because the longest research period in the literature is about 200 years, we test here the error variation of *n* changing from 1 to 300 years. Simultaneously, the effect of the different initial years m (i.e. initial stocks) on the error is also taken account. Hence, result error for each pair (*m*, *n*) will be presented.

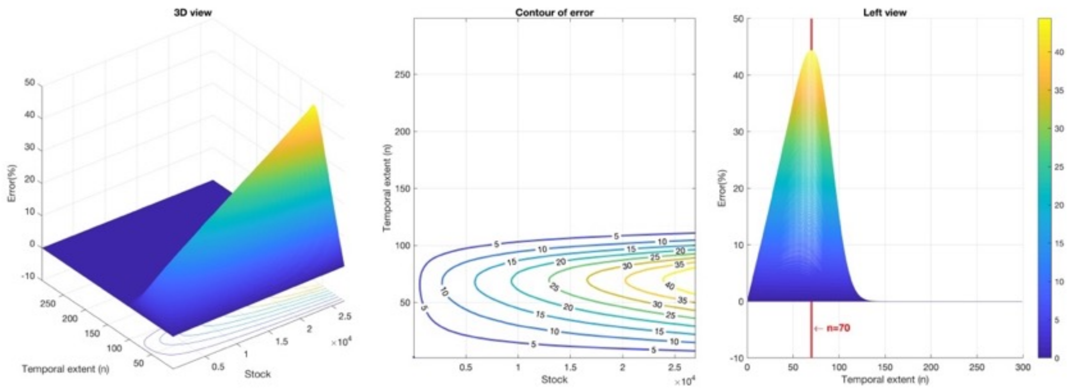
Considering the inflow-driven model, 600 random numbers around an S-shaped curve are generated as the inflows as we intend to include the error when m=n=300. Then follow the three steps described above, set the Normal distribution as the delayed pattern. The simulation is proceeded in the platform of Matlab. There are at least two interesting findings:

1) The error is positive in the most time except if m is really small with small amount inflow and stock at the far beginning (which is even not obvious in the figure). This indicates the stock is usually overestimated based on the initial assumption compared with the original dynamic MFA result that is calculated from the zero.

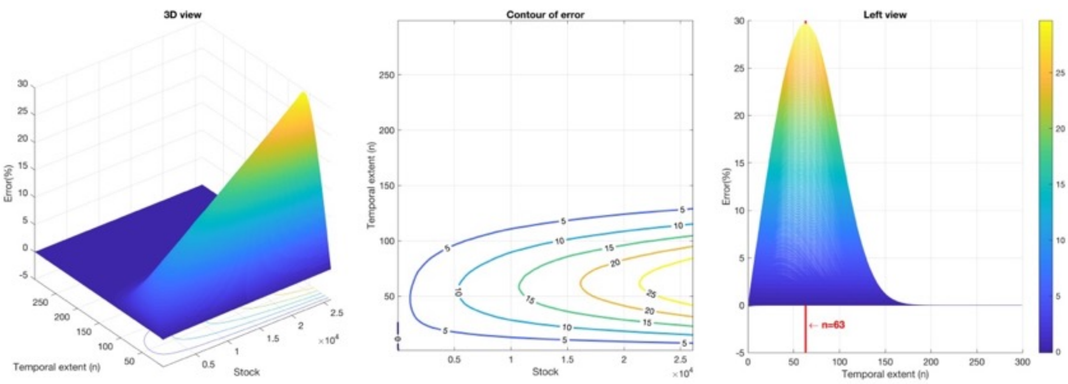




Mean=45, Std=15



Mean=90, Std=15



Mean=90, Std=30

Figure 12 Simulation results of different parameters

2) There seems a threshold for n. When n reaches a certain level, error is going to zero no

matter how much the initial stock is. And it is strongly related to the average building lifespan (μ) and less strongly to the lifespan standard deviation (σ). Though the exact threshold is still not possible, but a safe line can provide: n would better to be larger than $\mu + \sigma$. This finding challenges the results of some existing literature in which temporal extent is not long enough. Be careful, the above discussion is sourced from a very basic assumption that dynamic MFA model can capture the characteristics of reality perfectly. However, the truth may not be the case.

3.3.3 The Perpetual Inventory Method (PIM)

The buildings and materials stocked in them provide service for various economic activities. At the same time, they are also assigned with economic attributes through investment of well-designing, site survey, construction and so on. After the input of corresponding labor and material resources, completed buildings can enter the market as a commodity and be circulated. They are considered as a part of tangible produced fixed assets in economic domain as they are not consumed or destroyed during the actual production of a good or service but have a reusable value: buildings can survive for decades or they have long lifetime. Therefore, buildings are also estimated in the capital stock accounting.

In economics, to estimate production functions and measure total factor of productivity growth, capital stock accounting has been focused by massive literature (Jun Zhang 2008). Since the stock information is usually not directly observable (Berlemann and Wesselhöft 2014; Dalgaard and Thomsen 2003), the Perpetual Inventory Method (PIM) become the predominantly used technique to estimate gross fixed capital stock in many countries (Dey-Chowdhury 2008) with various enhancements and extension.

The PIM "consists of deriving the gross capital stock by having an initial stock in the far past and then keeping track of all the additions to and withdrawals (discards) from the capital stock" (Dalgaard and Thomsen 2003). It sounds really resemble with what dynamic MFA modeled, though some variant of PIM has been evolved and differed from case to case quite substantially (Berlemann and Wesselhöft 2014). Its basic idea can be expressed as followed.

$$K_t = K_{t-1} + I_t - D_{t-1} \qquad \textit{Equation 13}$$

where K_t is the capital stock at the end of period *t*, written as a function of the capital stock of the previous period K_{t-1}, gross investment I_t in *t*, and consumption of fixed capital, D_{t-1} which covers the value lose during the service life ends and ageing (depreciation). The consumption information of fixed capital is rarely available from the statistical office, same problem as we meet in the *Equation 5*. Assumed depreciation function as F, remaining function as $R = 1 - F$, we can rewrite the *Equation 13* as:

$$K_t = \sum_{c=1}^{t} I_c \times R(t-c) \qquad \textit{Equation 14}$$

Two depreciation functions have been commonly applied in a PIM: arithmetic (straight-line method) or geometric (reducing-balance method), cf. (Dey-Chowdhury 2008). The latter depreciation at a constant rate δ is the case in the most of existing literature (Barnhart and Miller 1990; Jun Zhang 2008). Therefore, the perpetual inventory formula is usually shown as:

$$K_t = (1-\delta)K_{t-1} + I_t = \sum_{c=1}^{t} (1-\delta)^{t-c} \times I_c \qquad \textit{Equation 15}$$

Although the depreciation function is problematic resulting in the error of the final stock, the PIM technique is still the mainstream of fixed capital stock accounting in various countries and regions. Compared between the dynamic MFA in industrial ecology and PIM in economics here, the core ideas appear quite similar. Both *Equation 6* and *Equation 14* can be generally explained as the certain stock is derived from the sum of all survived/remaining inflows from the far past to present with the assumed survivability or depreciation function. If we employ the same probability distribution into two methods, they will be the exactly identical model.

The great difference firstly lies on that the former measured in the physical unit like square meter or volume, while the latter estimated in the monetary value. Therefore, PIM needs to further consider the constant price adjustment which can be neglected in the building stock estimation. This also provide the potential to apply PIM into stock accounting in the industrial ecology in a simpler way. Secondly, PIM is a dynamic inflow-driven model, as the size of the present capital stock depends on the time series of investment data in the past. Its conduction requires the capital stock in the initial year and investment information for the following years as inputs. While dynamic MFA can be stock- or inflow- driven according to which data is easier accessible. Actually, in the early literature in the industrial ecology, similar method has been discussed as a branch of dynamic MFA – leaching model by Ester. She claimed this is static approach as "the size of the present outflow can be derived from the size of the present stock and no knowledge of the past is needed", which I don't agree, it's still dynamic.

To exemplify the validity of PIM, the historical data of the total building stock and newly completed floor area for residential buildings and non-residential buildings in Shanghai, a well-known municipality in China, are collected. Fortunately, the data is well available and in good quality. Because the newly completed floor area data is available from 1980, the building stock in this year is set as the initial stock. With the two methods of conventional dynamic MFA and PIM, the building stock is estimated for 1981 to 2016 separately. Lifetime function of Normal distribution with mean of 50 years and standard deviation of 15 years for dynamic MFA and depreciation rate of 3% for PIM are assumed. The comparison results are presented in Figure 13. It clearly shows PIM estimations are close to the statistical data (black dot-line), while dynamic MFA results have overestimations at the beginning stages and underestimations in the later years (red dot-line). The problem may lie on the assumption of the initial year, the delayed pattern and its parameters, or even the model structure is doubtable.

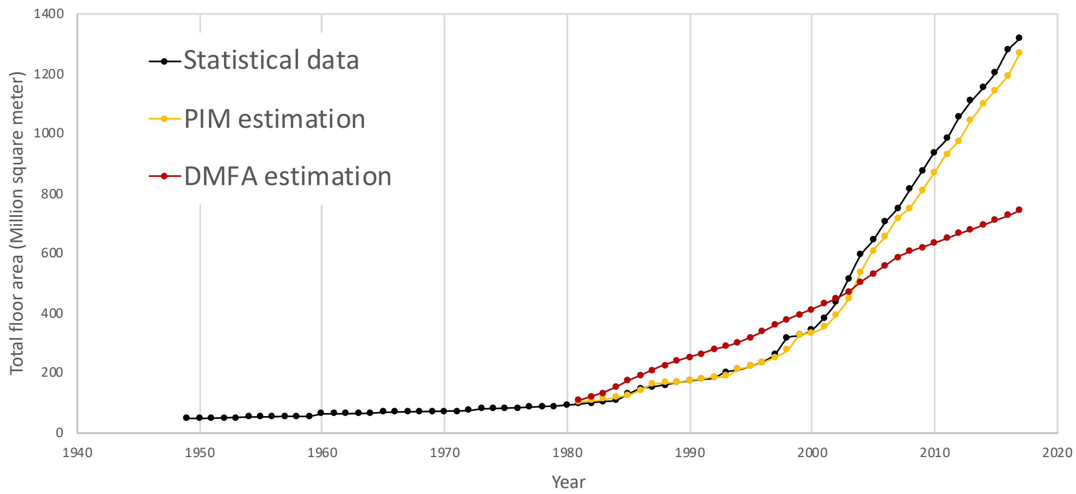


Figure 13 Empirical data and estimations for Shanghai

3.3.4 Dynamic method selection

If research goes far back in time, where stock was in the initial process of accumulation, $Stock_0 = Inflow_0 = 0$ can be assumed in the dynamic model. This, however, requires over hundreds of years series data hindering the research feasibility except for some new technologies or products, like electrical vehicles and smart phone, which was initially used in recent decades and starting point can be easily determined. Regarding the objects that has been existing in the society throughout the human history, like housing, such long series information is lost in most cases and the earliest year when the data can be obtained is usually considered as the initial year. If its composition and cohort's distribution is available, stock can be split into several cohorts as the input of the model, or else setting a warm up period is indispensable for eliminating the impact of initial stock. Moreover, the warm up period should not be shorter than the years of $\mu + \sigma$ theoretically, the time after that is what we can safely explain and analyze. But this is still really demanding for cases lack of time series data. In this research, PIM or leaching model is recommended as the robust substitution of decay model. Or static model may be a good alternative for short-term research because the dynamic approach is not to be preferred automatically over the more robust static approach (Vellinga, Berkhout, and Gupta 1998).

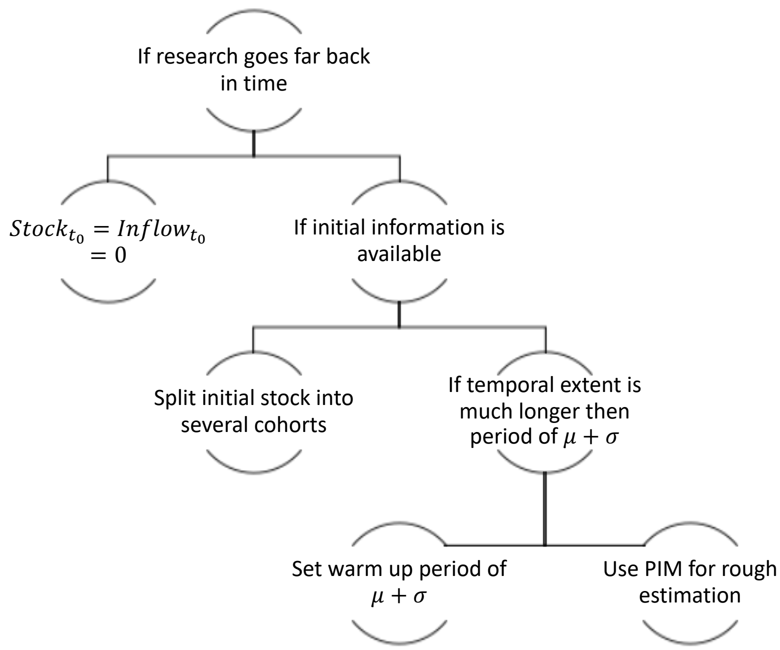


Figure 14 Schematic figure for method and assumption selection.

3.4 Material intensity

In the frame of bottom-up method, material intensity is one crucial coefficient for converting the physical number of end-use objects into mass stock and flow. In practical, MI varies with different building attributes of structures, building service types, construction years, regions and even case by case, which implies the uncertainty of MS results and we could never capture the real MS value. Scholars usually use average value as one important input of material stock and flow analysis, although they acknowledge the existence of error in results. To avoid the arbitrary determination of the MI, some research identified the probability distribution of material intensity and then produced material stock by Monte Carlo process through pseudo-random sampling, which reveals the uncertainty with providing the confidence interval. This, of course, greatly increased the amount of calculation. To choose either simple average value or pseudo-random sampling from distribution depends on the research question and data frame of physical number of end-use objects. Therefore, assumptions for MI in the following chapter are described for each due to different data frame.

4. Evolution patterns of urban building material stock and drivers

4.1 Method and data

4.1.1 PIM and parameters setting

As focus is over 200 cities in different socio-economic developing phases, such large number of cases must compromise with the sacrifice of long time series observation. Based on the aforementioned discussion about model's selection, here leaching model, or so-called PIM is used for the buildings MS estimation of Chinese cities. The spatial boundary covers the city area and subordinate towns and counties of the administrative area, hereinafter referred to as urban area of city. Subject to the data availability, time series from year 2000 to 2015 will be the temporal boundary. Building stock can be derived from the following equation:

$$RS_{i,t} = RS_{i,t-1} \times (1-\alpha) + RC_{i,t} \qquad \textit{Equation 16}$$

$$nRS_{i,t} = nRS_{i,t-1} \times (1-\beta) + nRC_{i,t} \qquad \textit{Equation 17}$$

where RS and nRS are residential and non-residential building stock, RC and nRC are newly completed floor area of residential and non-residential building respectively. Index *i* and *t* refer to the city and year. Particularly, α and β refer to the depreciation (demolition) rate for residential and non-residential buildings.

Converting building floor area stock to material stock requires the external coefficients of material intensity (MI). Since MI varies with different building structures, proportions of building structures are also necessary as inputs of model. See detailed discussion about MI and structure shares in following texts. The building MS can be estimated by the Equation.

$$MS_{i,m,t} = (RS_{i,t} + nRS_{i,t}) \times \sum_{j} (p_j \times MI_{j,m}) \qquad \textit{Equation 18}$$

where MS, MI and *p* refer to the material stock of buildings, material intensity and structure shares respectively. The type of material and building structure are denoted as *m* and *j*. Six kinds of materials (steel, cement, brick, sand, gravel and wood), and three types of building structures (brick-wood, brick-concrete, reinforced concrete) are mainly considered in this study. The schematic diagram of data frame and methodology is shown in Figure 15.

The uncertainty sourced from parameters of depreciation rate, MI and building structure shares results to the error of MS estimation. To reveal this uncertainty and yield the robust results, pseudo-random sampling is carried out for 10,000 times in Monte Carlo process, producing the mean of MS and its 95% confidence interval (CI).

The initial building stock $RS_{i,2000}$ and $nRS_{i,2000}$ comes from China Statistical Yearbook for Regional Economy 2001, and the newly completed floor area was compiled from the items of real estate industry and fixed assets of local statistical yearbooks for 215 cities. Non-residential buildings refer to all others except for residential use. Figure 16 shows the selected cities in green areas, 35 cities are in darker green including municipalities and provincial capital cities.

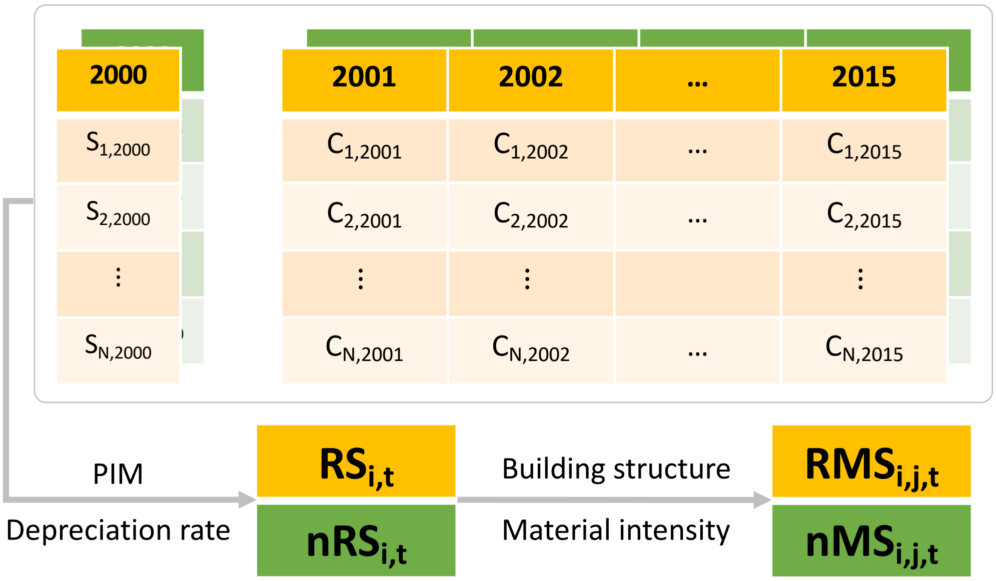


Figure 15 Schematic diagram of data frame and methodology

Figure 16 Selected cities in this study

Depreciation rate, material intensity and building structure are input parameters in above model, which lead to final estimation errors. To depict such uncertainty, assumptions and Monte Carlo process are conducted as described in the following.

Depreciation rate. The determination and assumption of depreciation rate have been substantially discussed in relevant research of PIM in the field of economics. It is usually set as the reciprocal of lifetime of fixed capital. However, such deterministic parameter reduces the capability of capturing the complex reality, which can be improved by random sampling. The residential buildings are designed to serve for 50 years. A number of researches claimed its lifetime is as short as 30 years in practical, although recent findings indicate the latest cohort might live longer because of better construction quality. Therefore, the depreciation rate of residential buildings α is assumed as a variable following the uniform distribution on [0.02, 0.03] in Monte Carlo process. With regard of non-residential buildings, its standard lifetime is 70 years, but experts believe that it can survive for only 40 years. Accordingly, the depreciation rate of non-residential buildings β is assumed to follow the uniform distribution on [0.025, 0.035].

Material intensity. MI varies with different building attributes of structures, building service types, construction years and even regions, which leads to inherent uncertainty and brings challenges for data collection. In order to simplify the data frame while entailing the principal information, it is necessary to understand which attributes strongly impact on MI, namely whether buildings with different properties have significantly different MI, but it has not been well documented yet. More investigations are required to be done for clarifying this question. Fortunately, a database of MI for Chinese buildings has been published online which contains 813 building samples with MI of ten kinds of materials, building structure, service type and construction years. Since the cohort information is missing in the initial year in this study, the MI under different construction periods are not considered. Therefore, this part is going to answer if buildings with different structures (brick-wood, brick-concrete, reinforced concrete) and service types (residential and non-residential) have different MI significantly from the view of statistics.

Multiple-way Multivariate ANOVA (Analysis of Variance) is applied to statistically test the differences between three or more group means for multiple dependent variables. In present case, the MI of six kinds materials are set as dependent variables, and building structures and service types are independent variables. With the help of SPSS, it is found that MI of different structures is significantly different. The effect of service type on brick intensity is statistically significant (P value <0.001), while the effect on other materials intensities is not. Thus, structure is concluded as the most important factor affecting MI when to fit the distribution for the intensities of six kinds of materials. According to the findings that structure is an important factor of MI, distributions by different structures are estimated for different materials. The best four distributions that fits data of MIs with BIC (Bayesian information criterion), AIC (Akaike information criterion), AICc (AIC with a correction for finite sample sizes) and corresponding parameters values are identified in the platform of Matlab[1]. Taking steel intensity of BC structure as an example, Figure 17 presents the its histogram and four best fitted curves, and detailed parameters are shown in Table 2. Considering that the values of MI are all positive, the logarithmic distribution is preferred- loglogistic and lognormal distribution. Furthermore, the loglogistic distribution with smaller BIC and AIC is selected for steel intensity. Similar process was done for other materials and their MI distributions is listed in Table 3. Histogram of other materials intensity for each building structures and best four fitted distributions are presented in Appendix 1. For those non-logarithmic distributions, if the sampling value is negative in the subsequent pseudo-random sampling, the absolute value is taken into the MS estimation model.

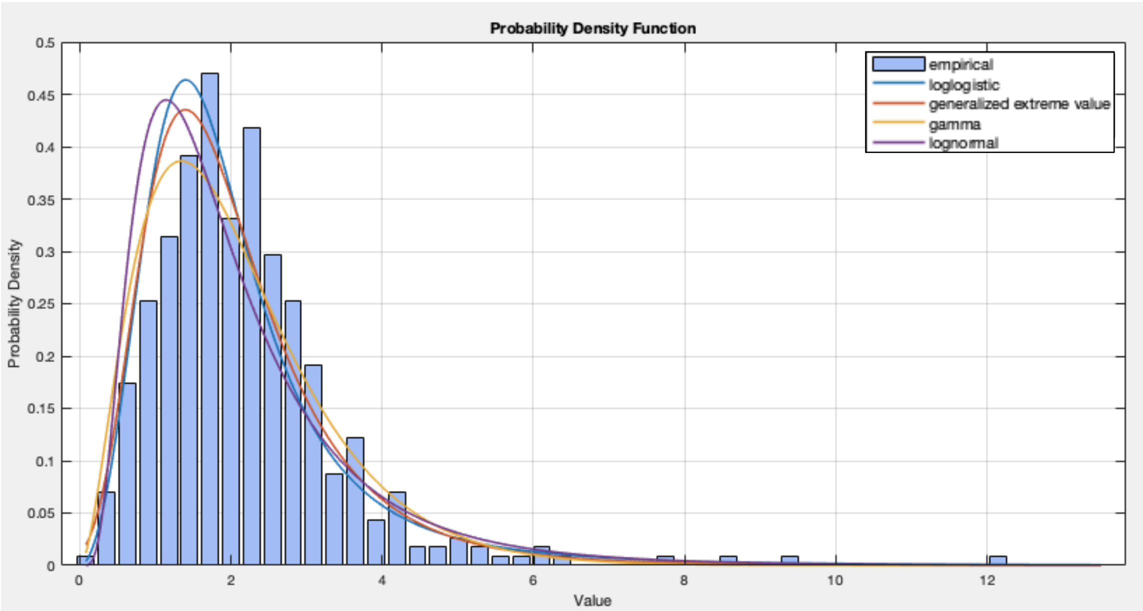


Figure 17 Histogram of steel intensity for BC structure and fitting curves

Table 2 Best 4 fitted distributions for steel intensity of BC structure

	Distribution 1	**Distribution 2**	**Distribution 3**	**Distribution 4**
Dist. Name	loglogistic	generalized extreme value	gamma	lognormal
BIC	1251.46	1251.52	1267.75	1284.32
AIC	1243.38	1239.39	1259.67	1276.24
AICc	1243.41	1239.45	1259.70	1276.27
Parameters Names	mu, sigma	k, sigma, mu	a, b	mu, sigma
Parameters Values	0.5780, 0.3403	0.1044, 0.8495	2.8511, 0.7258	0.5418, 0.6409

Table 3 Best fitted distributions for six materials intensity in different building structures

	Brick-wood	Brick-concrete	Reinforced-concrete
Steel	loglogistic	loglogistic	lognormal

[1] Yoav Aminov (2020). FBD - "Find the Best Distribution" tool (https://www.mathworks.com/matlabcentral/fileexchange/36000-fbd-find-the-best-distribution-tool), MATLAB Central File Exchange. Retrieved May 4, 2020.

	mu	sigma	mu	sigma	mu	sigma
	-2.3159	0.46764	0.57804	0.34029	1.4581	0.7638
Cement	Exponential		logistic		loglogistic	
	mu		mu	sigma	mu	sigma
	1.3909		14.065	2.63267	2.9033	0.26104
Brick	logistic		logistic		Weibull	
	mu	sigma	mu	sigma	a	b
	69.454	15.8813	81.6764	12.3662	48.6433	1.35402
Sand	loglogistic		loglogistic		loglogistic	
	mu	sigma	mu	sigma	mu	sigma
	3.1706	0.35962	4.0801	0.18491	3.9383	0.24703
Gravel	loglogistic		loglogistic		logistic	
	mu	sigma	mu	sigma	mu	sigma
	3.4092	0.52437	3.6339	0.31153	54.6906	14.8481
Wood	loglogistic		loglogistic		loglogistic	
	mu	sigma	mu	sigma	mu	sigma
	1.7002	0.265	0.43738	0.40911	0.7001	0.47725

Building structure. To correspond to the MI coefficients in various building structures, the proportion of structures in the building stock requires assumption. However, due to the lack of statistical data, we give some assumptions here. The three main structures currently used in China's building stock are brick-wood (BW), brick-concrete (BC), reinforced concrete (RFC) (Yang et al. 2020). Limited with the mechanical engineering strength, the BW structure is mainly used in the flat (1-3 stories) buildings constructed before the 1970s. Along with the widespread use of cement and concrete, BC structure became popular after the 1950s in China. But its seismic performance is still poor, so that mainly used for buildings below six stories. While RFC structure, emerging in 1970s in China, has strong adaptability and good seismic performance, so it can be used for multi-story, high-rise or even super high-rise buildings. Since a constant migration of people into cities in the process of industrialization and urbanization, cities tend to grow higher to meet the demand of human economic activities and good-quality life under the constraint of finite land resources. Accordingly, RFC structure has been more applied while BC structure was out of favor in recent two decades. Here, I assume the proportion of RFC and BC as logistic functions of per capita GDP:

$$RFC_{i,t} = 0.1 + \frac{0.65}{1 + e^{-(pgdp_{i,t} - 4)}} \qquad \textit{Equation 19}$$

$$BC_{i,t} = 0.8 - \frac{0.6}{1 + e^{-(pgdp_{i,t} - 4)}} \qquad \textit{Equation 20}$$

$$BW_{i,t} = 1 - RFC_{i,t} - BC_{i,t} \qquad \textit{Equation 21}$$

where $RFC_{i,t}$, $BC_{i,t}$ and $BW_{i,t}$ refer to the proportions of RFC, BC and BW in the building stock of city i and the year t, the sum of them is equal to one. The pgdp is the per capita GDP with the unit of 10^4 Chinese Yuan. The proportion of RFC is assumed to increase from 0.1 to the 0.75 (Equation 19), while that of BC would gradually decrease from 0.8 to 0.2 (Equation 20) with the growth of per capita GDP. The sigmoid's midpoint is set as 4 because the max value of per capita GDP in the period of 2000-2015 among the 215 cities is around 80 thousand Yuan. The change of structure proportions is shown in the Figure 18.

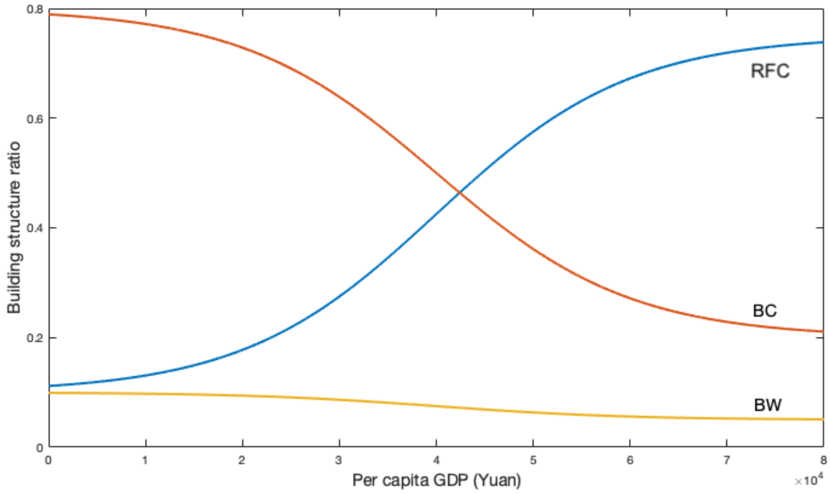


Figure 18 Evolution of structure proportions along with per capita GDP

4.2.2 Regression models

The classic IPAT identity indicates that population, affluence and technology are the main drivers affecting the environment. With the logarithm of IPAT identity for both sides of equation, the change of environmental impacts could be easily addressed by the sum of percentage of three determinants shifting, population, affluence and technology. GDP per capita is frequently employed as a proxy of the affluence driver. The technology is measured as “intensity”, namely the environmental impacts resulted from per unit of GDP growth, implying the smaller is better here regardless of rebound effect. Based on the cognition that global population and affluence are continually increasing, the positive effects on declining environmental impacts from technology innovation is offset by the faster and more phenomenal increment of those both. It seems impossible to environmental burden from anthropological activity, or to achieve so-called absolute dematerialization from this assumption and inference. Inversely speaking, absolute dematerialization limits economic growth rates (Steinberger et al. 2013), or human development has inevitably a lot to do with resource requirement, so the relative one may arise at the historical moment. Relative decoupling could happen that economic development outpaces the resource consumption. Accordingly, the population and GDP were selected as the primary explanatory variables in the following regression models.

(1) Panel regression model

In next step, I conduct an econometric panel analysis in order to uncover the nature of the long-term relationships of the evolution of urban building MS and urbanization. The classic IPAT identity indicates that population, affluence and technology are the main drivers affecting the environment. The urbanization that this study focuses on is implicit in the factor of population through the *Equation 22*:

$$upop_{i,t} = urb_{i,t} \times pop_{i,t} \qquad \textit{Equation 22}$$

where $upop_{i,t}$ and $pop_{i,t}$ refer to the urban population and total population of city *i* in year *t*, urb_{it} is the corresponding urbanization rate.

We are interested only in the effect of changes in population and economic activities on the ratio of change of urban building MS, particularly, population should be urban population in accordance with MS. To this end, we examine the logarithms of MS, urban population, and GDP. Our basic model is thus a multivariable panel regression:

$$\log(MS_{i,t}) = \alpha + \beta_1 \times \log(urb_{i,t}) + \beta_2 \times \log(pop_{i,t}) + \gamma_1 \times \log(gdp_{i,t}) + \varepsilon_{i,t} \qquad \textit{Equation 23}$$

where $MS_{i,t}$ is urban building material stock, $urb_{i,t}$ and $pop_{i,t}$ are urbanization rate and total population, and $gdp_{i,t}$ is gross domestic product of city *i* in year *t*. We extend the analysis by disaggregating the variables into more detailed components. In order to examine the effect of industry structure, the variable *gdp* can be substituted with the product value of secondary ($gdp2_{i,t}$) and territory sectors ($gdp3_{i,t}$):

$$\log(MS_{i,t}) = \alpha + \beta_1 \times \log(urb_{i,t}) + \beta_2 \times \log(pop_{i,t}) + \gamma_2 \times \log(gdp2_{i,t}) + \gamma_3 \times \log(gdp3_{i,t}) + \varepsilon_{i,t} \qquad \textit{Equation 24}$$

Furthermore, the material stocks of residential buildings and the non-residential buildings, and different materials have evolved in different ways, and may have different correlations with the explanatory variables. We examine the trends on residential buildings MS separately from non-residential buildings MS by adding two additional sets. As important construction materials with high carbon emission intensity, the trends of steel, cement and brick stock are also be observed in another three sets. Each set has two models similar to *Equation 23* and *Equation 24*, with different dependent variables. The modified Durbin-Watson statistic (Bhargava et al., 1982), Wooldridge test (Drukker, 2003), Pesaran test (DeHoyos and Sarafidis, 2006), likelihood ratio test showed time dependence, cross-sectional dependence in the data and heteroscedasticity across the panel. In light of this, we used robust Panel-Corrected Standard Error estimator (PCSE) (Mantobaye Moundigbaye, William S. Rea 2018).

(2) Threshold panel model

In the process of uncoordinated regional development of the country, the effect of the increase in urbanization rate on the urban building MS may show a non-linear relationship due to different stages of economic development, showing an interval effect. In order to avoid the errors caused by the artificial division of the urban economic development stage, this paper adopts the Hansen development threshold panel model, and divides the urban economic development stage endogenously according to the characteristics of the data itself.

$$\log(MS_{i,t}) = \alpha + \beta_1 \times \log(urb_{i,t}) \cdot I(pgdp_{i,t} \le \gamma) + \beta_2 \times \log(urb_{i,t}) \cdot I(pgdp_{i,t} > \gamma) + \delta X_{i,t} + \mu_i + \varepsilon_{i,t} \quad \text{Equation 25}$$

Equation 25 is a single threshold effect regression model with different economic development levels. The multi-threshold model can be expanded on the basis of *Equation 25*. Whether a single threshold or multiple threshold model is used needs further verification. In the formula: X is a set of control variables that have a significant influence on MS, here is the total population and GDP same with the basic panel regression model in *Equation 23*; the indicator function $I(\cdot)$ represents different levels of urban economic development, *pgdp* is the threshold variable, γ is the threshold level to be estimated; μ is the individual effect; ε is the random error term.

The threshold variable is mainly set to divide the level of urban economic development. As the most common indicator for representing the stage of economic development in the world, per capita GDP is widely used in international and regional organizations such as the World Bank. It is also commonly used in research to characterize the regional economic development, providing insight to capture the overall nature of regional economic development. Therefore, per capita GDP is set as the threshold variable indicating the difference in economic development.

4.2 Results

4.2.1 Material stock evolution

The construction materials stocked in urban buildings in 215 Chinese cities almost tripled from 17.73 billion tones in 2000 to 49.29 billion tones in 2015. Yearly urban building MS additions have been showing in the Figure 19. The net MS addition kept a constant increase trend from 1.1

billion tons per year to 3.3 billion tons until the last two years, when it emerged a slight drop, averaging with 2.1 billion tons a year throughout the 16 years. With regard to the construction materials, the important components of concrete, cement, sand and gravel, has been over triply accumulated, reaching 32.4 billion tons accounting for 65.7% in 2015. As a material for reinforcing structure, steel has been more applied than before, resulting to 4.7-fold increase (0.23 to 1.09 billion tons) during the short period of time. While brick accounting for 37.5% of overall MS in 2000 doubled to 15.07 billion tons and comprised 30.6% in 2015. This change can attribute to the evolution of building structures as explained above (Figure *18*). The wood has always been in a small proportion (1.3-1.5%) as a kind of non-structural material.

Figure 20 presents the MS proportions by service types and MS dynamics by city groups. The net MS addition to the residential buildings varies between 0.72 to 1.2 billion tons in each year. While that of non-residential buildings increased from 0.39 billion tons in 2000 and surpassed residential MS addition in 2006, followed by a fast growth to 2.57 billion tons until 2015. Even in 2013, there emerges a peak of yearly MS addition in non-residential buildings while a valley for residential buildings, which is possibly resulted from the state regulation of the real estate market and strict control of housing prices, thus, there was a temporary downturn in real estate investment. Unsurprisingly, the non-residential MS accounts for more 10% in 2015 than the beginning year, implying more investment flowed into non-residential buildings to improve the public service and production facilities while ensuring accommodation for the surge of people. To uncover the different characteristics of MS trend among different types of cities, I group the 35 major cities that aggregate a great number of people and economic activities, including municipalities, provincial capital cities and cities specifically designated in the state plan, and compare them to the rest of cities. The urban building MS in 35 major cities generally accounted for 42-46% of the total MS. It goes up faster than the rest of other cities before 2008, but the case was reversed after that. 60% MS addition happened in other median and small cities in the period of 2008-2015. This would be attributed to the China unveiled its ever-largest fiscal stimulus package to housing and major infrastructures to avoid the wrath of the 2008 Global Financial Crisis, and medium-small cities took more advantages from this initiative due to more land resources for city construction compared with almost land-saturated mega cities.

Per capita MS of urban buildings increased from 47.3 tons per person in 2000 to 77.9 tons in 2015. This values in 35 major cities are always higher than rest other cities throughout the 15 years and such gap has been widen especially in non-residential stock (Figure 21). Although a considerable scale of construction has been achieved in median and small cities especially after 2008, they were the major destinations of urbanization, newly accommodating 248.5 million immigrants from rural areas in these 15 years. 35 mega cities have only adopted 46.4 million immigrants but with 45% MS addition. During the year of 2010 to 2015, per capita MS of non-residence expanded rapidly and outpaced the residential stock in both mega cities and under-advanced cities, which is consistent with the total MS evolution (Figure 20).

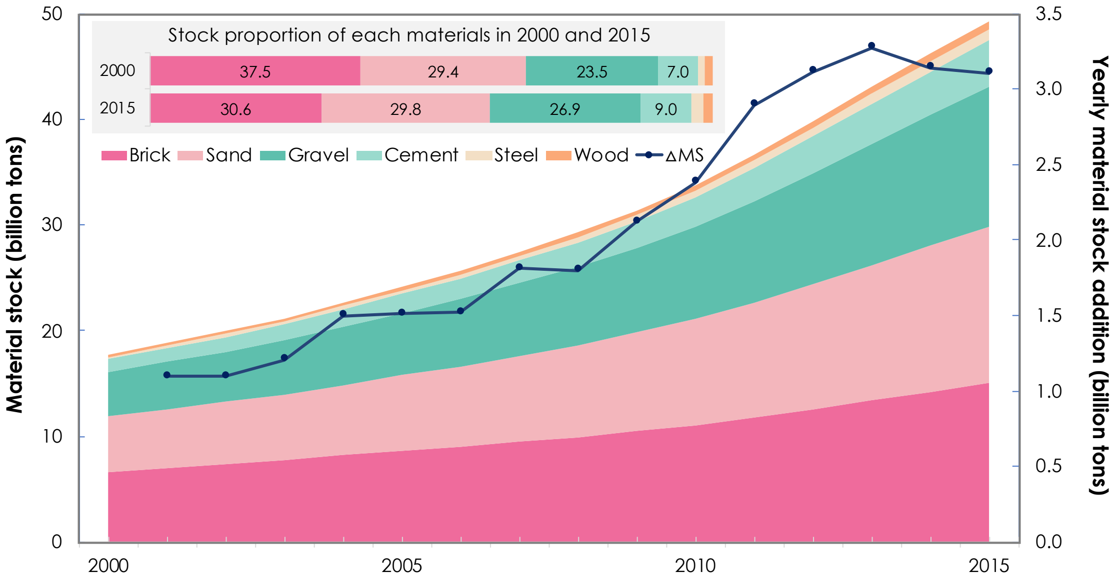


Figure 19 Urban building MS by six primary materials (left vertical axis) and yearly MS addition (in line, right vertical axis). The subplot in the upper left corner shows the comparison of MS proportion of each materials between 2000 and 2015.

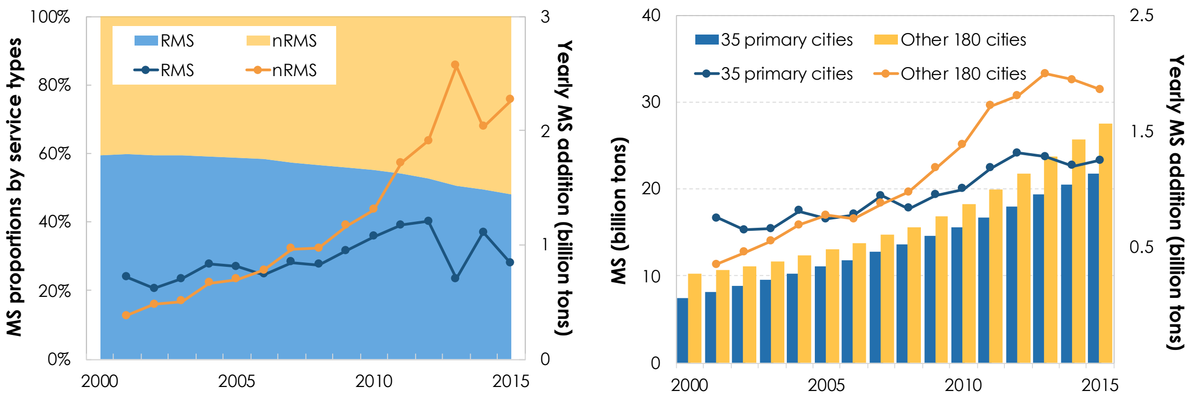


Figure 20 MS dynamics by service type (left) and city group (right)

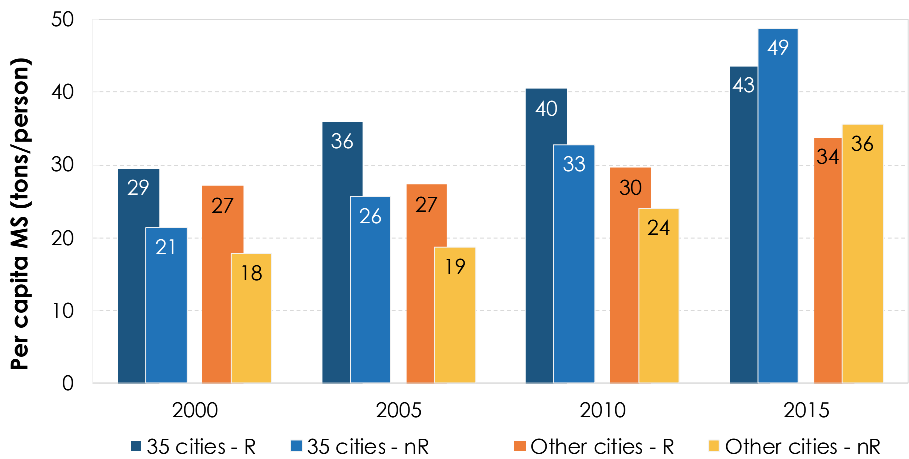


Figure 21 Per capita MS of each city group and service type (R: residential; nR: non-residential)

4.2.2 Panel analysis results

The results of the panel regressions are presented in Table 4. Urbanization shows a positive correlation with urban building MS and overall it explains most of the growth of MS in model (1): 10% increase of urbanization rate (*urb* in the Table 4) is correlated with a 6.95% increase in urban building MS, ceteris paribus. Relative decoupling of MS accumulation from population is apparent, a population (*pop*) increase of 10% is correlated with 3.27% MS growth. The small coefficient of GDP (0.116) seems suggesting a strong relative decoupling trend of MS from economic activities. If we substitute GDP with the industry structure in model (2), the vast majority of MS growth is still caused by urbanization (0.75) and the coefficients of the population and territory sectors are close (0.299 and 0.247 respectively). The coefficient of secondary sector (-0.082) is negative but very small, indicating increase of secondary sector product is weakly correlated with MS decline. However, contribution of secondary sector has been dropped in most of cities in recent years. Industry upgrade or transformation has been promoted to develop the industry with less intensive resource use and more economic benefits. Meanwhile the industry of intensive material uses and pollution is shrinking, most of which is in secondary industry. Therefore, the negative coefficient is not delightful because the decline of the secondary industry will cause an increase in the stock.

The MS of residential and non-residential buildings evolves in different trends and paces as depicted above. Using the same two model specifications as described previously we proceed to examine building MS of two service types in model (3)-(6). Comparison of the two model sets shows urbanization has remarkably stronger correlation with non-residential building MS than residential building MS, indicating urbanization requires more space constructions for working, education, health care and other services to improve the living quality and citizen well-being in contemporary China. Unsurprisingly, the same effect pattern happens to the territory sector on two kinds of MS, although the coefficients are smaller. While the larger coefficients of population in RMS models (3) and (4) show the effect of population change on residential building MS is bigger that its non-residential counterpart. Overall, the expansion of quantity in population first tends to drive the residential building MS, the structure transformation from rural population to urban residents would be the main demand of the non-residential building MS. The coefficients of secondary sector in two sets are all negative but close to zero, very weak effect on MS change.

Similar fashion was further used for examining the three materials - steel, cement and brick stock in (7)-(12). Urbanization explains the most of stock accumulation for these three materials,

Table 4. Coefficients obtained from the results of PCSE regressions.

	MS		RMS		nRMS		Steel		Cement		Brick	
X	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
urb	0.695***	0.750***	0.540***	0.566***	0.969***	1.023***	0.305***	0.375***	0.497***	0.562***	0.878***	0.916***
	(0.0332)	(0.0349)	(0.0314)	(0.0329)	(0.0491)	(0.0490)	(0.0380)	(0.0340)	(0.0311)	(0.0311)	(0.0377)	(0.0397)
pop	0.327***	0.299***	0.319***	0.299***	0.259***	0.232***	0.244***	0.216***	0.294***	0.265***	0.322***	0.298***
	(0.0278)	(0.0267)	(0.0215)	(0.0219)	(0.0391)	(0.0392)	(0.0509)	(0.0451)	(0.0361)	(0.0317)	(0.0262)	(0.0268)
gdp	0.116***		0.123***		0.136***		0.252***		0.179***		0.0633***	
	(0.0243)		(0.0185)		(0.0360)		(0.0376)		(0.0303)		(0.0204)	
gdp2		-0.0821***		-0.0300***		-0.0774***		-0.0832**		-0.0887***		-0.0625***
		(0.0147)		(0.0108)		(0.0233)		(0.0329)		(0.0215)		(0.0142)
gdp3		0.247***		0.186***		0.262***		0.385***		0.319***		0.168***
		(0.0258)		(0.0176)		(0.0375)		(0.0426)		(0.0323)		(0.0226)
t	0.0271***	0.0184***	0.0187***	0.0127***	0.0334***	0.0245***	0.0517***	0.0419***	0.0386***	0.0290***	0.0178***	0.0106***
	(0.00472)	(0.00430)	(0.00308)	(0.00291)	(0.00713)	(0.00657)	(0.00720)	(0.00664)	(0.00589)	(0.00539)	(0.00371)	(0.00344)
Constant	8.444***	8.378***	7.914***	7.909***	7.996***	7.943***	3.969***	3.962***	5.687***	5.641***	7.791***	7.724***
	(0.226)	(0.184)	(0.171)	(0.157)	(0.296)	(0.238)	(0.431)	(0.369)	(0.311)	(0.249)	(0.174)	(0.157)
R-squared	0.970	0.971	0.970	0.971	0.957	0.958	0.967	0.969	0.970	0.971	0.968	0.969

Note: Numbers in parentheses are the standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 Threshold effect test and threshold level estimation results

	MS						RMS						nRMS					
	(1)			(2)			(3)			(4)			(5)			(6)		
	Single	Double		Single	Double		Single	Double		Single	Double		Single	Double		Single	Double	
F statistics	284.5***	139.2***		193.4***	107.1***		122.4***	40.7*		77.9***	33.4		314.6***	151.0***		250.8***	120.7***	
P value	0.00	0.00		0.00	0.00		0.00	0.09		0.007	0.257		0.00	0.00		0.00	0.00	
Threshold	81.6	56.5	87.5	63.5	56.5	87.5	87.5	56.5	90	87.5	87.5	4.1	57.1	50.4	85.8	57.1	49.8	81.6
Lower	68.8	55.8	85	62.7	55.8	85	85	55.2	87.4	85	85	4	56	49.6	82.3	56	49.2	80.4
Upper	83	57.1	89	64.5	57.1	89	89	57.1	92	89	89	4.2	57.7	50.9	87.5	57.7	50.2	83

especially regarding the brick, 1% urbanization growth is correlated to around 0.9% brick stock increase in urban buildings, showing stronger effect on brick stock than cement and steel. The coefficients of population in three model sets are close to each other but brick stock would increase slightly more than cement and steel stock for each population expansion. While we found the inverse order of coefficients of GDP and territory sector product. Economic growth, especially the growth of the tertiary industry, tends to stimulate the steel stocks in urban buildings more greatly, followed by cement. But it is less correlated to the brick stock growth. These three regression sets interpret that an increasing number of urban populations requires larger stock size, effecting strongly on those materials accounting for a large proportion, while economic development is more likely to change the material composition, using more steel and cement for new constructions due to more high buildings emerging in cities.

4.2.3 Threshold regression results

The threshold regression model is used to examine the non-linear effects of urbanization on material stock accumulation under different economic development levels. In this part, we mainly show the regression results of total material stock in urban buildings (MS), residential building material stock (RMS) and non-residential building material stock (nRMS). Table 5 shows the F statistic and P value obtained by "bootstrap method" under each threshold setting, as well as the threshold level estimation and confidence interval obtained by the maximum likelihood estimation method. The effect of the single and double threshold for MS and nRMS sets are very significant with the corresponding P values less than 0.01. Regarding the RMS models, the single threshold effect is significant but double threshold not. Therefore, the double threshold effect regression is performed on MS and nRMS, single threshold modelling for RMS. To simplify the description, we divide the economic development into three stages of low, middle and high according to double thresholds.

According to the threshold effect regression results presented in Table 6 with per capita GDP as the threshold variable and dividing the levels of economic development, the effect of urbanization on material stock is significantly different under different economic development levels. When the per capita GDP is less than 56.5 thousand Yuan, the coefficient of urbanization rate is 0.962 and 0.948 in two MS models respectively, and changes to 0.623 and 0.651 along with the increase of per capita GDP. But after it reaches a threshold of 87.5 thousand Yuan, the urbanization does not have effect on MS anymore. We interpret these results as that in economically underdeveloped areas, urban infrastructure is also relatively deficient such as poor housing conditions, insufficient medical, education and entertainment venues, etc. Therefore, more construction investments into these urban areas are required in the process of urbanization. When the economy develops to a certain extent and there has been a certain amount of capital accumulation, the elasticity of urbanization on stocks would decrease, that is, the rate of construction change will decrease for each urbanization rate increase. This model set even shows

Table 6 Regression results under threshold effects

	MS		RMS		nRMS	
X	(1)	(2)	(3)	(4)	(5)	(6)
pop	0.422***	0.383***	0.378***	0.348***	0.387***	0.372***
	(0.0475)	(0.0468)	(0.0459)	(0.0454)	(0.0645)	(0.0642)
gdp	0.196***		0.199***		0.214***	
	(0.00747)		(0.00684)		(0.0103)	
gdp2		-0.0353**		-0.00610		-0.00935
		(0.0137)		(0.0133)		(0.0188)
gdp3		0.240***		0.210***		0.231***
		(0.0148)		(0.0140)		(0.0204)
urb_1	***pgdp*≤56.5**		***pgdp*≤87.5**		***pgdp*≤49.8**	***pgdp*≤50.4**
	0.962***	0.948***	0.677***	0.664***	1.325***	1.304***
	(0.0289)	(0.0293)	(0.0275)	(0.0280)	(0.0392)	(0.0400)
urb_2	***56.5<pgdp*≤87.5**		***pgdp*>87.5**		***49.8<pgdp*≤81.6**	***50.4<pgdp*≤85.8**
	0.623***	0.651***	0.144***	0.233***	0.843***	0.889***
	(0.0362)	(0.0365)	(0.0518)	(0.0531)	(0.0463)	(0.0469)
urb_3	***pgdp*>87.5**				***pgdp*>81.6**	***pgdp*>85.8**
	-0.0598	0.0778			-0.0373	0.158**
	(0.0548)	(0.0563)			(0.0726)	(0.0691)
Constant	6.681***	7.091***	6.162***	6.530***	6.200***	6.482***
	(0.273)	(0.271)	(0.263)	(0.263)	(0.370)	(0.371)
R-squared	0.827	0.833	0.775	0.781	0.804	0.807

that the urbanization becomes uncorrelated with material stock once the per capita GDP comes to a high interval, which signifies that the material stock at contemporary stage could not change no matter how the future urbanization evolves.

However, the models breaking MS down to the RMS and nRMS provides more interesting information. There is a single threshold in RMS set though, it is significant that RMS correlated with urbanization more strongly at low and middle level of per capita GDP, compared with high stage. The results of nRMS models present similar change of urbanization effect on material stock from low economic stage to high economic stage. A comparison between two model sets (2)-(6) found the coefficients of urbanization in nRMS regressions are bigger than that in RMS ones before per capita GDP enters high stage. After that, the effect of urbanization on housing MS has become smaller but still significant, while its effect on nRMS is uncertain in this study.

The requirement by urbanization for residential MS remains large at the beginning and middle phases of economic development, which is the basic urban function of accommodating rapidly growing residents. At the same time, non-residential MS also keeps increasing at a much faster rate. When cities grow toward the advanced stage, urbanization still has demand on residential MS but may not for more non-residential part. Generally speaking, the marginal construction investment of urbanization reduces along with the constant MS accumulation, that is, the required material stock will decrease for each additional unit of urban population.

4.3 Discussion

4.3.1 Material stock and waste management in developed cities

35 primary cities are the large possessor of material accumulation although its net addition was surpassed by rest of cities in later years. According to empirical results, the regions with higher economic development levels may decouple future urbanization from stocks. In other words, developed cities will no longer face the problem of urban construction in the future, instead, stock management can be their challenge. Large-scale built environment not only requires constant material and energy input for its maintenance and operation, but also has higher possibility of demolition waste generation. It is imminent to complete the waste management regulation and support the recycling business, as scholars have suggested. Before the policy is formulated, it is

necessary to fully understand the quantity, composition and spatial distribution of current building material stock, which is studied in next chapter.

4.3.2 Material stock accumulation and shrinking cities

Results of empirical analysis reflects construction investment and material accumulation was closely related to urbanization in the past, especially in economically underdeveloped cities. If this pattern continues, the future urbanization of these areas may require more resources input for new construction of both residential and non-residential buildings. For the investments of resources to support the necessary social development, reducing its environmental impact can be achieved by long-term urban planning, efficient use of resources, and building designing. The latter two expect to promote the recycled material use and new technology for buildings, which required stakeholder's collaboration of engineers, architects, governments, etc. While scientific urban planning is conducive to keep buildings providing services for a long time, avoiding large-scale demolition and re construction in a short term, and reducing the resources use and waste generation as much as possible. This is a blueprint and prerequisite toward sustainable city, but tricky compared with the other countermeasures because it's government-oriented and involves China's land finance system[2].

Most cities are growing with more residents, while a few of cities as shrinking in present China, either in resource-based cities, or traditional industry cities, or less developed regions (Long and Wu 2016). They are undergoing population lose, but these local governments still make plans under the hypothesis of growing population and more constructions are implemented. It is conceivable that these buildings may not be effectively used or even wasted. Perhaps there are fewer such cities, which are not reflected in the empirical results. This is beyond the scope of this study, but draws a discussion of what to do for those cases.

[2] That is, only by predicting future population growth can local government get improvement to develop land for construction.

5. Present spatial patterns of building material stock in metropoles

As discussed above, wealthy regions may no longer face the problem of urban construction in the future, instead, stock and waste management can be their challenge. Before the relevant policy is formulated, the quantity, composition and spatial distribution of current building material stock is necessary to fully understand and study. Therefore, the building MS for the 14 metropoles in Eastern China was calculated with GIS-based static bottom-up method of year 2017.

5.1 Selected metropoles

Due to the lengthiness to properly establish a GIS database, selecting the most representative cities is crucial to meaningfully investigate the building MS of a fast-paced developing nation. According to the National Bureau of Statistics, China can be divided into four regions: East (E), Central (C), West (W), and North-east (NE), as plotted in Figure 22 (National Bureau of Statistics of China 2014). Eastern China accounts for over half of the national GDP, one third of the whole population, and approximately 48% of the national built-up floor space; at the same time, its per capita GDP and urbanization rate also surpass the other regions and hauls the national indicators in 2016 (Table 7). Economic surge and urbanization process often correspond to a large material consumption to meet the growing demand (Fishman, Schandl, and Tanikawa 2015). About 50% of constructions took place in Eastern China, suggesting that its consumption of construction materials, water, electricity, and natural gas are concentrated in this region. Therefore, focusing on Eastern China is a good way to grasp the rapid-paced development currently happening in China and provide insights for other less-developed regions in the country.

Eastern China includes 3 municipalities (Beijing, Shanghai, and Tianjin) and 7 provinces (Hebei, Jiangsu, Zhejiang, Shandong, Fujian, Guangdong, and Hainan). To selected representative cities, the law of primate city[3] is employed to find out the primate cities which can provide good

[3] Geographer Mark Jefferson developed the law of the primate city to explain the phenomenon of huge cities that capture a large proportion of a country's population as well as its economic activity (Jefferson 1989). Chinese scholars referred this concept analyzing the provincial variation of urban primacy and spatial agglomeration of population and economics (Leng et al. 2011; C. Gu 1992).

feedback in terms of regional development and MS characteristics. The primary index[4] for 6 Eastern provinces is reported in

Table 8, and with the exception of the province of Fujian, where the largest city is Xiamen, the capital city corresponds to its primate.

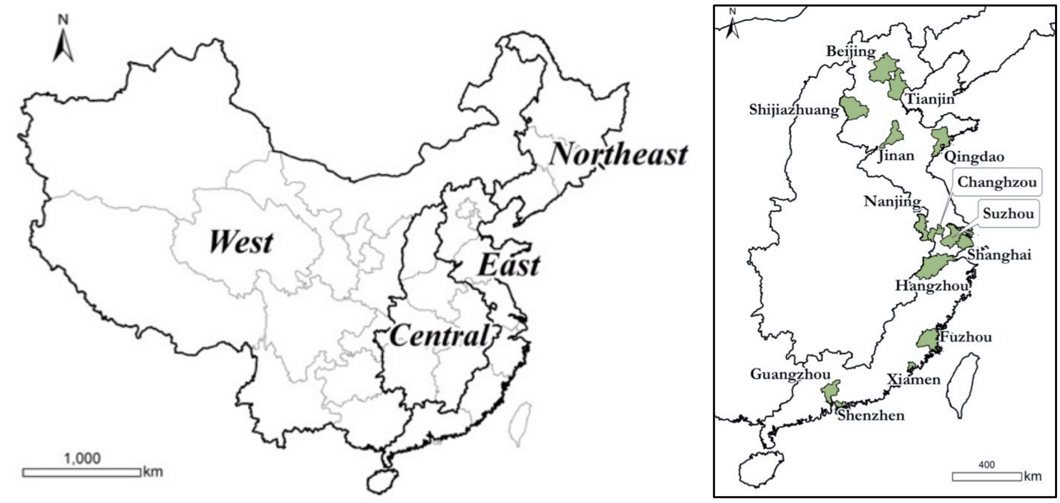


Figure 22 The four major geographical regions of China and location of the selected 14 cities in Eastern China

Table 7 Share of main socioeconomic characteristics by regions in 2016[5]

Region	Percentage of each region (%)							Per capita GDP (Thousand, in 2016 current Yuan)	Urbanization rate (%)
	GDP	Population	Built-up area	Floor space completed	Water consumption	Electricity consumption	Natural gas consumption		
E	52.58	38.37	45.74	47.61	53.07	48.82	59.49	77.47	65.94
C	20.59	26.60	20.15	21.85	19.09	18.45	13.71	43.76	52.77
W	20.10	27.11	23.01	25.32	19.00	26.70	22.91	41.92	50.19
NE	6.72	7.90	11.11	5.22	8.83	6.03	3.89	48.04	61.67
China								53.98	57.35

Table 8 Primate cities and primary indexes for the Eastern Provinces

Province	Hebei	Jiangsu	Zhejiang	Shandong	Fujian	Guangdong
Capital city Primate city	Shijiazhuang	Nanjing	Hangzhou	Jinan	Fuzhou Xiamen	Guangzhou
Primary index	1.39	2.09	1.69	1.15	1.25	1.18

[4] It is calculated as P_1/P_2. P_1 and P_2 refers to the population of the largest city and second one respectively according to Mark Jefferson. Here we used the data of population in urban districts sourced from China City Statistical Yearbook 2017, excluding Hainan.

[5] Data source: China Statistical Yearbook 2017

In the present study, we firstly selected the aforementioned 3 municipalities and 6 primate cities of each province and, with regard to the three provinces of lower primary index (Shandong, Fujian, and Guangdong), we included the next largest city, namely Qingdao, Fuzhou, and Shenzhen respectively. Furthermore, two notable prefecture-level cities, Suzhou and Changzhou, ranking 3rd and 9th in the list of per capita GDP among 89 Eastern cities and accommodating over 1,000 people per square kilometer, have also been considered in this study. In total, 14 cities were selected for this MS analysis, and together they account for 45% of the GDP and 36% of the population of Eastern China.

The available data for these cities did not cover the entire administrative boundaries of the municipality, but only their central districts. These areas are hubs characterized by enormous amount of infrastructure and buildings, which shape the city's character and its resource consumption pattern (Fernández 2007). To ensure that the available data was correctly covering the cities' downtown areas, we first checked the urban master plans, and confirmed this with a hotspot analysis.

The location of the selected 14 cities is displayed in Figure 22. Shanghai and Beijing are the two most populous cities of China, counting over 20 million residents in each metropolitan area. They went through decades of population growth but, for the first time in 2017, experienced a halt. This is likely due to a recently approved urban master plan aiming to rein population growth in those metropoles (Beijing Municipal Bureau of Statistics 2017; Shanghai Municipal Bureau of Statistics 2017). If this policy were to be kept for the upcoming years, we could have reached a point of saturation for the resident population, which could then trigger construction in the peripheral areas. The remaining 12 cities of our study all include a considerable number of inhabitants. Even Xiamen, the smallest of the selected 14 metropoles, has a population of over 4 million, which is more than the total population in Mongolia in 2017 (World Bank 2018). These 14 cities together accommodated around 12% of the Chinese population, but generate almost a quarter of the national GDP, resulting to an average GDP per capita that is more than double the rest of the country.

Additionally, data on the built-up area is an indicator of the urbanization progress. The 3 municipalities (Beijing, Shanghai, and Tianjin) and the city of Guangzhou have the largest built-up area. Some other cities, like Qingdao and Xiamen, have smaller built-up areas, but grew more than doubled during the past decades according to the data from the China Urban Construction Statistical Yearbook. The floor space of completed buildings in the 12 cities we have data of (data is not available for Suzhou and Changzhou) accounts for 16% of the whole 1,061 km^2 of completed floor space in China in 2016, indicating the great expansion of the built environment these metropoles experienced, which was accompanied by large extraction, consumption and accumulation of construction materials, alongside with plenty of water and energy consumption.

5.2 Method and data

5.2.1 GIS-based material stock

The total in-use building MS can be obtained by multiplying all inventory items and their respective material intensity coefficients. Recently Metrodata Tech Company provided GIS data of buildings located in the central areas of the major cities in China of year 2017 referring Gaode Map (https://www.amap.com/), which include the shape, location, and number of stories of each building. This data can be used to evaluate the total material stock by multiplying it with the average material content per unit of floor area, as shows in *Equation 26*:

$$MS_m = \sum FA_j \times MI_{j,m} \qquad \textit{Equation 26}$$

Where MS_m is the total mass of the material m; FA_j refers to the total floor area of building type *j*; and $MI_{j,m}$ is the material intensity, namely the content of material *m* in per unit of floor area of building type *j*.

To precisely estimate the MS, accurate MIs should be employed for each specific structure type, functional type, and built-year. However, such detailed information is not available and in most cases was estimated. Hu categorized 1-6 story buildings as masonry-concrete structures, and 7+ story buildings as steel-concrete structures according to the consideration of earthquake resistance, durability and cost (D. Hu et al. 2010). In Shi's study, the authors supposed that half of all the buildings constructed after 2000 in China are composed of a reinforced concrete (RC) structure (Shi et al. 2012).

In this study we employ a calibrated version of the MI database developed by Shi and colleagues as it includes both residential and non-residential buildings. Buildings are firstly discerned into brick-concrete and RC on the basis of the number of floors as suggested by (D. Hu et al. 2010). Next, the weighted average of the MI is calculated keeping into consideration the proportion of residential/non-residential buildings and construction cohort. With regard to the share of service types, Hong and colleagues pointed out that the total floor space of residential buildings is approximately double the floor space of commercial edifices excluding public buildings (Hong et al. 2016). As the central area of a city typically provides more non-residential services compared with the whole average, we assumed an equal share of 50% for each type, and therefore the MI of buildings has been calculated as the mean of MIs of these two types. As for the division by cohort, the 2010 population census indicates that over 93% of the total floor area was built after 1980 (cf. Figure 23). The MI coefficient of the latest cohort in Shi's research was weighted averaged to obtain the calibrated MI for brick-concrete and RC buildings according to the above-assumed equal share of building service in this study, shown in Table 9.

Table 9 Calibrated average material intensity (kg/m^2)

Structure	Cement	Steel	Sand	Gravel	Wood	Brick	Total
Brick-concrete	193.5	24.5	719	561.5	29	623	2150.5
RC	328	77.5	619	815.5	26.5	125	1991.5

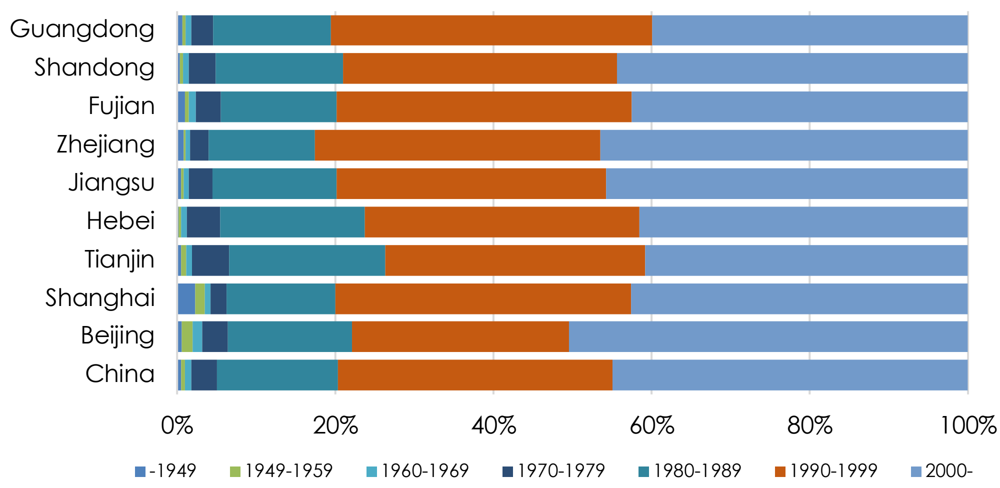


Figure 23 Proportion of constructed floor area by cohort in 2010 for China and relevant provinces.

5.2.2 Population estimation

To unpack the relationship between MS and the amount of people benefitting from it, it is necessary to know the number of people living within our study areas. These areas comprise only the central part of each city, yet population data is available only at the municipal level, making necessary the estimation of the population living within the boundaries of the areas of analysis. To do so, we employed *Equation 27*:

$$P_i = \sum_{j=1}^{N} P_j \times \frac{S_{ij}}{S_j} \qquad \textit{Equation 27}$$

where P_i is the population in the i-th study area; P_j denotes the population in district j in 2017; S_{ij} is the overlapped area of study area i and administrative district j; S_j indicates the area of district j.

It is important to mention that official statistics on population refer to the resident population only, excluding commuters. This clearly will have an impact on the results of per capita building MS: some city centers will have more tertiary-dedicated edifices than others and will thus count fewer residents. This will be taken into account in the sensitivity analysis.

5.2.3 GIS spatially explicit tools

Buildings require a lot of natural resources for their construction, impacting macroscopically on the urban form and transportation, and microscopically on the energy used for heating, cooling, lighting, and appliances. The spatial distribution of the building stock could provide a first glance for urban planners to better understand their cities. The GIS data in present study provides the capability to allocate the spatial distribution of building MS, plotting on a map the level of accumulation and highlighting focal nodes of the city. To support this spatial analysis, we calculated the Global Moran's I index and performed a hotspot analysis through the use of a GIS software. The spatial resolution of the analysis is 500m for all the 14 areas object of our study. The Global Moran's I index is the most commonly used statistical test of spatial autocorrelation (Lee 2017; Zeng et al. 2015), namely whether cluster occurs in a given area and its surrounding area, where positive values validate the presence of cluster and vice versa, with the range from 1 to -1. Furthermore, hotspot analysis identifies statistically significant clusters (define as hot spots and cold spots) in the map. In this case, MS clusters would reveal the centers and scale of human activity and socioeconomic development. From the perspective of environmental sustainability, MS cluster tends to consume more energy and emit more greenhouse gas, leading to warmer microclimates (Ichinose and Liu 2018; Kennedy et al. 2015). Therefore, identifying those clusters will provide useful foundation for resource managers and urban ecologists who strive for a sustainable resource consumption and the counteraction of the heat island effect.

5.3 Results

5.3.1 Building MS

The results of the estimation are printed in Figure 24. The overall amount of materials stocked within the study areas was estimated to be 7.9 billion metric tons (cf. Figure 24A), where over one third is located between Shanghai (1.7 Gt) and Beijing (1.3 Gt). Unsurprisingly, gravel, sand, brick and cement, bulk materials primarily used for construction, account for 34%, 31%, 17%, and 13% of the MS respectively. In total they account for 95% of the whole mass, similarly to the 93-96% range estimated by Chen and colleagues (Chen et al. 2016). Steel (3%) and timber (2%) constitute the remaining part. Gravel, sand, and cement are mixed together to produce concrete, chief component of modern constructions, especially in Asia. We find that concrete constitutes 78% of the total mass, aligning our results with previous studies of MS in Asia-Pacific, 90% in Taipei, 70% in Japan and 91.8% in Melbourne, but differ sensibly from the findings in Europe, around 40% in case of EU25, Germany and Vienna, 32% in Padua and only 22% in the UK (S. L. Huang and Hsu 2003; Tanikawa and Hashimoto 2009; Kleemann et al. 2016; Miatto et al. 2019; Wiedenhofer et al. 2015; Stephan and Athanassiadis 2018). This confirms the clear difference in typical construction methods between Asian and European countries.

Stock density, displayed in Figure 24C, varies between 1.6 and 2.8 Mt/km^2 (mean: 2.1 Mt/km^2, standard deviation: 0.4 Mt/km^2), according to the location and scale of each area. Downtown areas are often densely filled with high-rise buildings like shopping malls and offices, while peripheral areas have fewer tall rise buildings. This suggests that, for larger study areas, the MS density would be lower than for smaller ones focused on city centers. Results show that, however, this is not always the case. The study area of Shanghai covers 666 km^2, exceeding all of the other cities included in our analysis, yet its stock density reached 2.5 Mt/km^2, indicating the presence of densely distributed and high-rise buildings even in areas far from downtown. A similar result was found for Guangzhou and Shenzhen, whose stock density amounts to 2.7 and 2.8 Mt/km^2 respectively. Figure 24D also shows the per capita building MS for each city center. Compared to

210 t for each Viennese resident in 2013 (Kleemann et al. 2016), 8 cities in this study present a higher MS per capita, averaging 238 t/person, which is also higher than the results in last chapter perhaps because the population here is underestimated for urban center area. The highest values have been recorded in Guangzhou, Hangzhou, Suzhou, and Changzhou, exceeding 300 t/person. This value is higher than the average of Japan calculated by Tanikawa and colleagues, who estimated 323 metric tons per capita of MS including both buildings and infrastructure, suggesting that the Japanese MS related to building is below the values discovered by this study (Tanikawa et al. 2015). This indicates that the MS of buildings in these highly urbanized areas has reached and surpassed the level of developed countries.

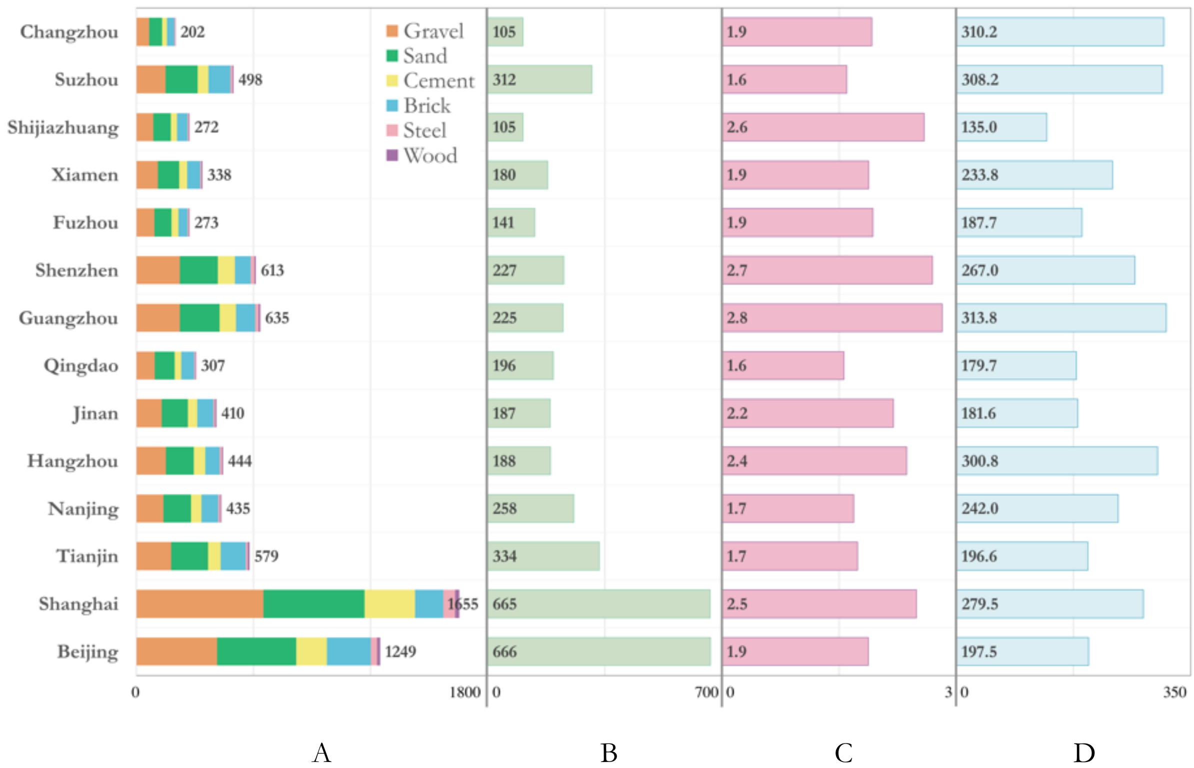


Figure 24 A: Total building stock (Mt); B: study area (km²); C: Material stock density (Mt/km²); D: Material stock per capita (t/cap).

The aforementioned results are based on the assumption of an equal share of two service types and an evenly spread population on the municipal territory. To assess the impacts of these assumptions, we conducted a sensitivity analysis altering the share of type and population. Lowering the residential building share to 40%, 30%, 20% generated a respective shrink of the total stock of -1.1%, -2.2%, -3.3% (**Error! Not a valid bookmark self-reference.**). An alteration of the population in the study area of ±10%, ± 25% resulted in a MS change of -9% ~ 11%, -20%~33% respectively. Accounted service share in, the average per capita MS could be reach minimum as 184 t/person.

Table 10 Sensitivity analysis of stock, average per capita MS for the service share and population in the central area

Share (R:NR)	Cement %	Steel %	Sand %	Gravel %	Wood %	Brick %	Total MS Gt (%)	Average per capita MS with different population change (t/cap)				
								Default	±10%		±25%	
5:5							7.9(0.0)	238	216	-9%	190	-20%
									264	11%	317	33%
4:6	2.2	2.9	-1.6	-0.2	3.4	-2.6	7.8(-1.1)	236	214	-10%	188	-20%
									262	10%	317	33%
3:7	4.4	5.7	-3.3	-0.4	6.9	-5.3	7.7(-2.2)	233	212	-11%	186	-21%
									259	9%	311	30%
2:8	6.7	8.6	-4.9	-0.6	10.3	-7.9	7.6(-3.3)	230	209	-12%	184	-22%
									256	7%	307	29%

5.3.2 Building MS spatial distribution

From a resource and waste management perspective, the spatial distribution of materials is as important to know as the overall amount of stocked materials. This information allows for an accurate prediction of the amount and composition of CDW arising during the construction and demolition activities of specific areas, including the estimation of the quantity of secondary raw materials.

With help of a GIS software, we identified that the MS of all cities are significantly clustered with a 99% confidence level, but there are minor variations among them. The Moran's I index of MS density in Beijing is the highest, indicating a higher density of MS compared to other cities (cf. Figure 24). The hot spot analysis revealed where highly dense MS is clustered as hot spot in the map. For brevity, we report in the main manuscript the results of Tianjin, Jinan, and Shenzhen as examples, while the figures for the remaining cities can be found in the supplementary information.

Table 11 Moran' I index of the spatial distribution of material stock

City	Beijing	Shanghai	Tianjin	Guangzhou	Xiamen	Fuzhou	Qingdao
Moran's I	0.657	0.647	0.621	0.603	0.589	0.579	0.562
City	Jinan	Nanjing	Shenzhen	Hangzhou	Changzhou	Suzhou	Shijiazhuang
Moran's I	0.515	0.493	0.485	0.475	0.471	0.455	0.439

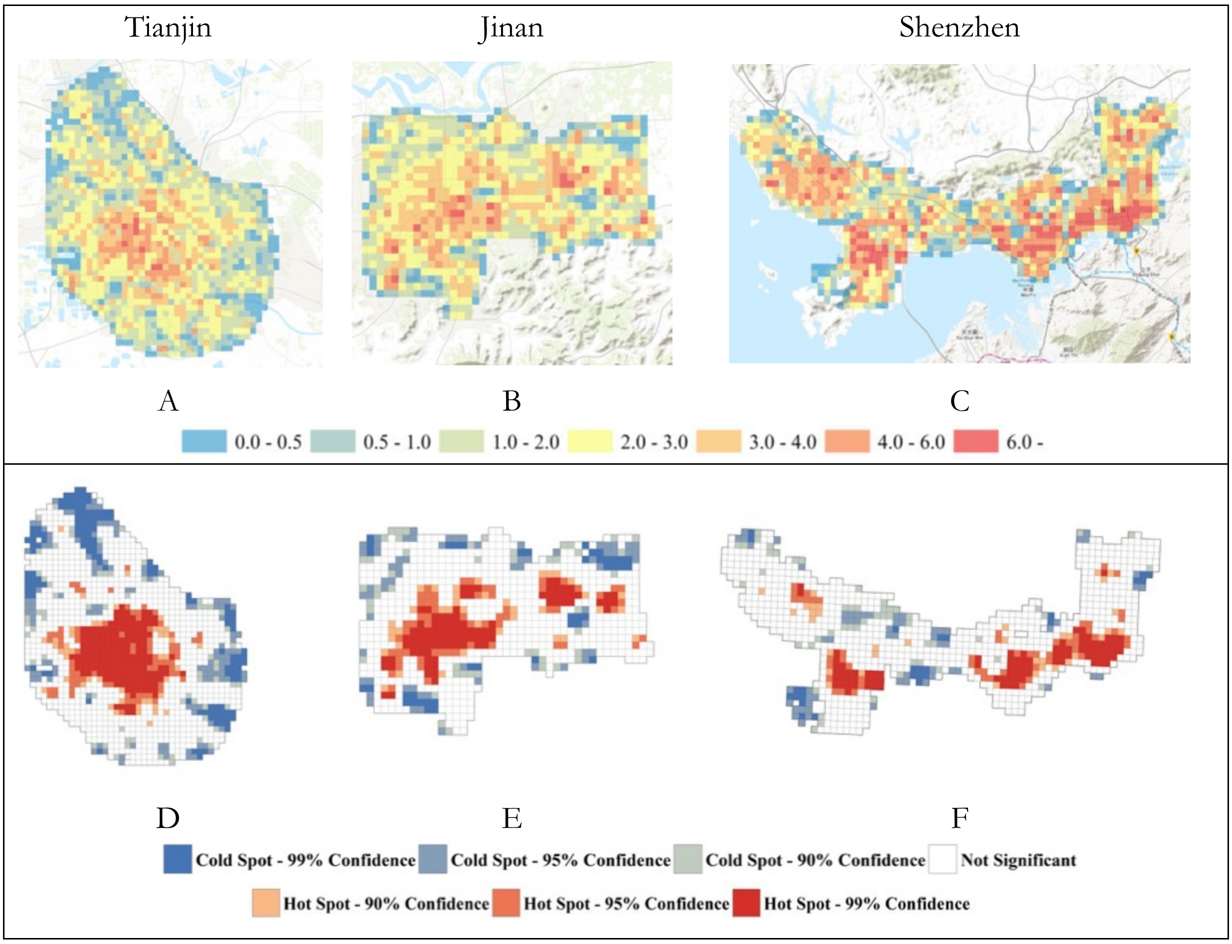


Figure 25 A, B, and C: material stock distribution for buildings in the study area (Mt/km2) for Tianjin (A), Jinan (B), and Shenzhen (C). D, E, and F: hotspot analysis for Tianjin (D), Jinan (E), and Shenzhen (F).

Figure 25A, 5B, and 5C reported the spatial distribution of MS density. The areas in red indicate a high MS (more than 6 Mt/km^2), and are often an indicator of downtown areas and financial districts. Conversely, blue areas represent a low stock (up to 0.5 Mt/km^2), and are often found in the more peripheral areas of the metropoles. Figure 25D, E, and F presents the results of the hotspot analysis. Red areas denote high MS density clusters while blue areas correspond to low value clusters. We classified the cities in three types: where there is a single hotspot (type 1), where there is a major hotspot and minor ones (type 2), and where there are multiple major hotspots (type 3). The three cities shown in Figure 25 correspond to these groups. This analysis provides the basis for policy makers of each city to formulate management strategies, and supports city planners to understand the urban spatial structure.

5.3.3 Socioeconomic relation with MS

Cities are places where the MS tends to accumulate, and their maintenance and expansion is of great concern to environmental strategists. Figure 26 plots the relationship between MS per capita and GDP per capita of our 14 study areas. Results show that GDP and MS both tend to increase on a per capita level, at least until 150,000 CNY/cap (approximately 21,810 USD/cap in 2017). The two entries on the right, Suzhou and Shenzhen, show a slight decline in MS/person against a growth of GDP. It is not clear whether there is an effective dematerialization after a certain level of wealth, or this is simply an idiosyncrasy of these two cities. No regression analysis was conducted here because of the small sample that could lead to biased and invalid results. We however calculated the Pearson correlation coefficient[6], which resulted to be 0.78, indicating that more developed cities accumulate more materials to provide both basic needs and further requirements to more affluent residents.

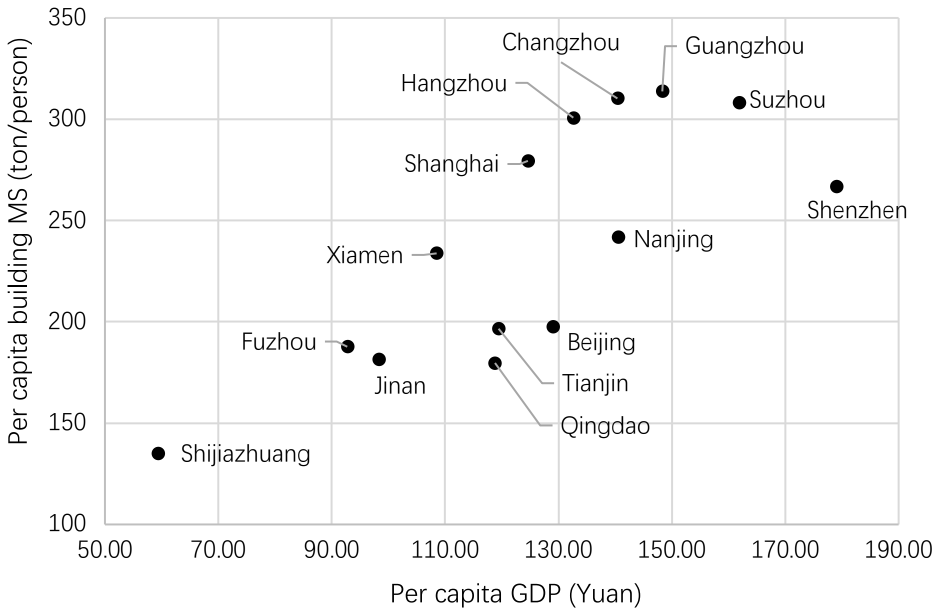


Figure 26 Relation between GDP and MS in per capita terms for the 14 cities object of our study

[6] The Pearson correlation coefficients is a measure of the linear correlation between two variables X and Y, and varies between -1 and 1. A value of -1 indicates a total negative linear correlation, of 0 indicates no correlation, and of 1 a total positive linear correlation.

5.4 Discussion

5.4.1 Informing future environmental strategy

The positive correlation between per capita MS and GDP, on the one hand, suggests that decision makers from wealthier cities would better be relying on a city plan that tightly controls construction activities, and sets an early warning for future construction waste that should be properly treated. On the other hand, it also informs the still-developing cities of Central and West of China, where the MS of buildings does not come anywhere near the amount found in the Eastern metropoles, that environmental impacts of resource consumption should be considered before the booming of the local economy. Otherwise plenty of resources invested into construction could prematurely turn into waste, which may be beyond the local waste management capacity. Therefore, a society which is sustainable both from an environmental and economic prospective should be set up, aiming at an effective resource use, conservation, and recovery. This should be seen as an opportunity to create urban plans that consider urban sprawl, prioritize resource conversation, efficient transportation networks, and ecological sustainability.

5.4.2 From MS to CDW: waste management warning

As discussed in section 5.4.1, waste management is one of the areas where city planners should focus. The outflow of materials from the built environment, namely demolition waste, is generally estimated using lifetime probability functions. In China the design lifetime is required to be 50 years for residential buildings and 70 years for commercial buildings. Yet studies based on actual data show that the reality is very different and residential buildings in China are demolished after only 30 years (Song 2005; Hong et al. 2016). Some researchers found that it might be even less: Cai and colleagues calculated, through the analysis of statistical data on annual built floor area and total floor area, that the average lifespan of buildings could be as short as 23.2 years (Cai et al. 2015). In present study we estimated the presence of 7.9 Gt of construction materials. Assuming that even only half of the buildings were built before 2000, these older constructions would generate at least 2 Gt of demolition waste by 2050 based on the optimistic 50-year design lifetime. How can policy makers properly manage these large flows of secondary resources? All these materials can be recovered, and buildings should be interpreted as repositories of natural resources for the future (Marcellus-Zamora et al. 2016; Ortlepp, Gruhler, and Schiller 2016). However, in China CDW is usually illegally dumped or disposed in landfills, and only about 5% of CDW is recycled (B. Huang et al. 2018), due to lack of rigid regulations ranging from collection, sorting, treatment to ultimate disposal (Duan and Li 2016). It appears clear that the 14 metropoles we studied will face the serious challenge of CDW disposal, which will rapidly become of extreme relevance, and which could be faced in a sustainable way only if appropriate plans of waste management, reuse, and recycling will be set in place.

Meanwhile, the lengthening of the lifespan of existing buildings, at least to the design period, would translate in less resource extraction, with clear benefits for the environment in terms of quarrying, biomass removal, and a loss of the natural habitat of wild animals.

6. Construction material flows and stocks over space and time

To better investigate the trends and change of construction material flow and stock over space and time along with socio-economic development, and find how to tackle conflicts between development and sustainability, building-by-building the material flows and stock accumulations was chronicled in high-resolution 4d-GIS database for the Tiexi district of Shenyang, a microcosm of China's urban transformations since the early 20th century.

6.1 Historical context: The rise, fall, and rise of Tiexi

Shenyang is the capital city of Liaoning Province, with an urban population of 8.3 million (Shenyang Bureau of Statistics 2018). It is a core manufacturing industrial city in China due to the historical development of the Tiexi district, known as *the eldest son of Chinese industry* and *the Eastern Ruhr* (M. Wang et al. 2013). Its history can be traced back to the late 19th century, when Russia forcibly occupied a patch of land of 6 km^2 in Shenyang for constructing the railway in Northeast China. In 1905, Japan took over this area and started urban planning and exploitation under the puppet Manchukuo Regime. The initial colonized area was expanded and formally set up as the Tiexi (铁西区 lit. West of the Railway) industrial zone in 1932, with a layout of factories in the North and workers' accommodations in the South (Xiong 2017). It became an essential industrial site dominated by Japanese-owned enterprises. Following Japan's defeat by the Soviet red army in

1945, most equipment and raw materials of Japanese-owned factories were taken away to the Soviet Union, resulting in the closing or suspension of 95% of factories by 1948 (M. Wang et al. 2013).

From the foundation of New China in 1949 to the early 1970s, the Chinese central government made use of the legacy of Tiexi's colonial industrial base, directing its development toward heavy industry as a key national project (Ren et al. 2015). During this time, Tiexi was the country's most important industrial base, representing its highest technical levels and manufacturing capacity, as well as exporting support for other industrial zones in terms of equipment and skilled workers. These contributions and achievements are considered remarkable to the industrialization and modernization of New China (M. Wang et al. 2013).

The Tiexi industrial zone started deteriorating after China's reform and opening due to a path dependency of state-owned enterprises, structural imbalance of heavy and light industry, and shifts in domestic economic policies and priorities (Ren et al. 2015; P. Y. Zhang 2003). Efforts of the central and local governments to upgrade technologies and reform state-owned enterprises in the Tiexi industrial zone from 1986 to 2001 largely failed and it experienced a continuous recession (M. Wang et al. 2013). The Shenyang municipal government decided to reform the whole industrial zone in 2002 by merging the old Tiexi District (39 km^2) with the Shenyang Economic Development Zone (SEDZ) as New Tiexi (484 km^2) and relocating enterprises from the historical Tiexi to the SEDZ (Ren et al. 2015). The Tiexi old industrial zone was replaced with high-rise residential and commercial buildings from 2002 onwards (Xu et al. 2019). This striking process is reflected in the district's economic transformation. The secondary sector was the main contributor to economic output in the Old Tiexi District throughout nearly the entire 20th century until a dramatic drop in the late 1990s. From 2009, along with the completion of revitalization project in the past decade, the commercial services tertiary sector started to take off, reaching around 80% by 2013 (Jing Zhang 2009; Shenyang Bureau of Statistics 2017; L. Wang 2018). Our case area is the 10 km^2 of the old industrial zone (Figure 27). "Tiexi" in the following sections points to this area if there is no special description.

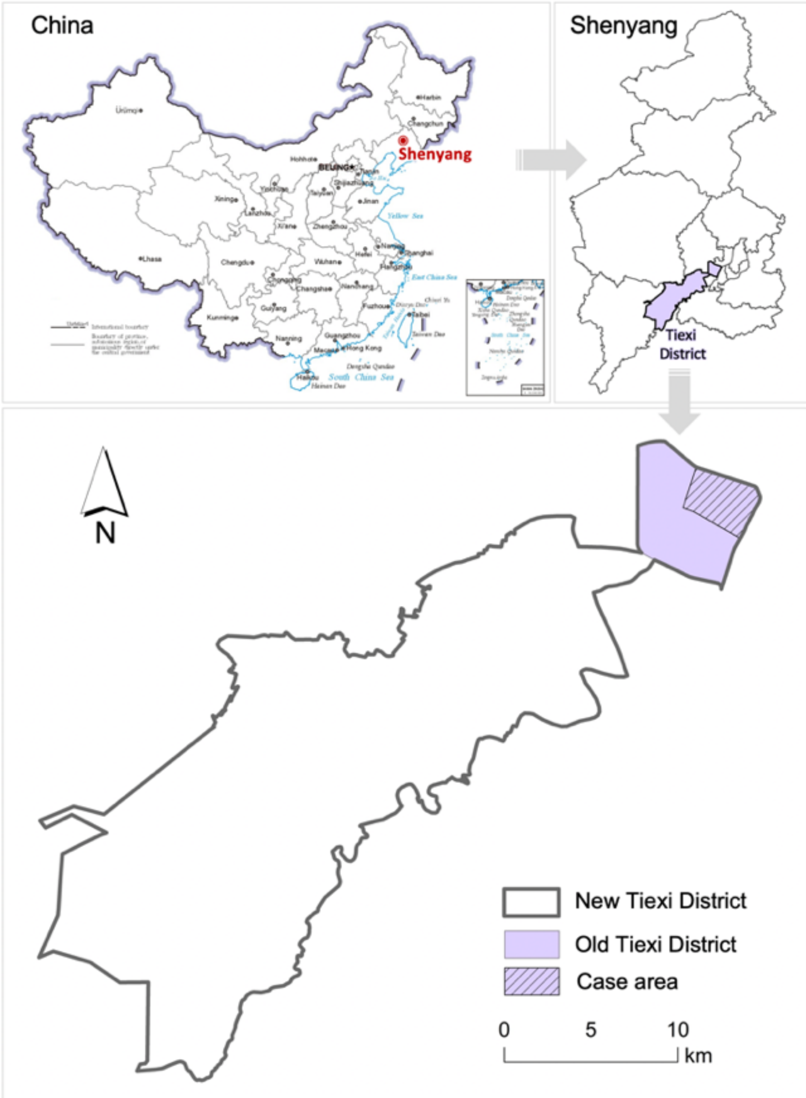


Figure 27 The location of case area in Tiexi, Shenyang, China

6.2 Method and data

6.2.1 Compilation of building cohort snapshots

We compiled "4d-GIS" (four-dimensional geographic information system) material stock data (Tanikawa and Hashimoto 2009) composed of 12 snapshots of the material stock of Tiexi from the founding of the Tiexi district ca. 1910 through 1932, 1947, 1968, 1978, 1986, 1997, 2002, 2004, 2008, 2011, to 2018. A flowchart of the method is available in Figure 28. Complete details of data sources and uncertainty levels are described in the Appendix. The 4d-GIS approach requires high-resolution geo-data (building by building) and precise attributes for each building. Data compilation was done in a retrospective manner, working backwards from the newest and most recent cohort to the earliest one, because the information of present buildings was easier to obtain through existing datasets and digitalized maps. Using these methods each building could be traced back with its attributes, including service type, and floor number/height to its earliest appearance.

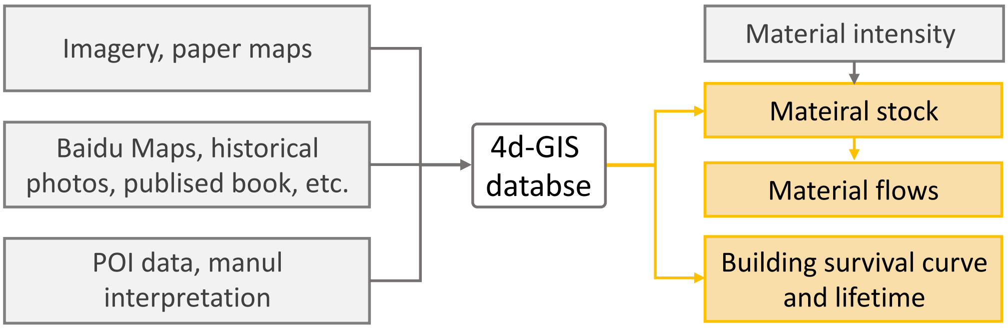


Figure 28 Flowchart of the 4d-GIS method. In light grey are the external data, while in orange the endogenous datasets and output of method.

The locations and shapes of buildings were vectorized based on satellite imagery and aerial imagery in recent years, and paper maps in the earlier years. Historical paper maps, print photos, aerial photos, satellite imagery, existing GIS data, as well as documentary materials were collected, digitized, georeferenced, and cross-linked in the ArcGIS application suite. For instance, buildings in the maps from 1997 or later that do not appear in 1986 means that those buildings were newly completed during 1986-1997 and are assigned as the cohort of this building period.

The typologies of buildings, namely industrial, residential, or other (commercial or public) use, were identified with Points of Interest Data for the latest three cohorts of 2008, 2011, and 2018. For the preceding snapshots, typologies were ascertained using visible characteristics or information of buildings from satellite imagery or map sources. For example, industrial buildings are recognized through their characteristic blue roofs, and with descriptive titles of buildings that are presented on the map.

Building height is available from Baidu Maps for 2018. With this advantage, the unknown heights of buildings of the 2002-2011 cohorts were estimated based on their shadow and the known heights of buildings from 2018 dataset. Heights were converted to floor numbers with the assumption of an average of 3.5 meters per floor, which was further used to determine the building structure (brick-concrete or reinforced concreted in Table 12) using to the method employed in (J. Guo et al. 2019). Floor numbers in the earlier datasets was collected directly from documented floor numbers in materials from government sources, historical photos from published books, and related description from survey reports, etc. For buildings still missing this attribute an averaged floor number of that era was assigned.

6.2.2 Material stock and flow calculation

Each building's material stocks in units of mass were estimated as the product of the building floor area by appropriate material intensity coefficients using *Equation 28*.

$$MS_{c,i,j,m} = TFA_{c,i,j} \times MI_{c,i,j,m} \qquad \textit{Equation 28}$$

where MS is the material stock of a building, *TFA* is its total floor area, and *MI* is the material intensity coefficients. The indices *c*, *i, j* and *m* are the construction period, building structure, building functional type, and construction material respectively.

The material intensity (*MI* in the above equation) is the mass per square meter, and in practice is unique to each building. Similar values may generally be found for buildings of distinct categories by function, construction structure, period built, and other architectural principles and so we assume MIs represented by the average MI values for each cohort, functional typology, and building structure. We compiled typical Material Intensity (MI) coefficients by these three attributes , resulting in 24 classes, with averages from *China's Building Material Intensity Coefficient Dataset* which contains over 800 cases of different buildings with their material intensities including foundations (Yang et al. 2019). We include eight kinds of construction materials: sand, gravel, cement, brick, steel, timber, lime, and glass. Lime is used for bottom layer of the building foundation. If the above referenced dataset does not cover a certain category (e.g. MIs before 1950), alternatives are supplemented from the Construction Project Investment Estimation Handbook (Yu and Li 1999). The MIs of commercial buildings before 1990 are not included because of the scarcity of such buildings when the study area was an industrial base with a small number of houses for workers. The MIs are documented in detail in *Table 12*.

Total material stock (MS), and MS by cohorts, functional types, and construction materials can be easily derived by summing up the material stock of buildings belonging the corresponding category. For instance, MS by cohort and total MS in year of snapshot *t* were calculated with *Equation 29* and *Equation 30*.

$$MS_{t,c} = \sum_{i,j,m} MS_{c,i,j,m}$$ *Equation 29*

$$MS_t = \sum_{c,i,j,m} MS_{c,i,j,m}$$ *Equation 30*

For the earlier cohort, 1910, the material inflow is equal to the material stock of that year. Buildings newly appearing in a consecutive snapshot are accounted as a new cohort of inflows (*Equation 31*). We then track the disappearance of these buildings in succeeding snapshots to quantify the survival trends of cohorts. Buildings that do not appear in a subsequent snapshot period were deemed to have been demolished in the interval and their materials are accounted as outflows of that interval (*Equation 32*).

$$Inflow_t = \sum_{i,j,m} MS_{c,i,j,m}\ , \qquad if\ c = t$$ *Equation 31*

$$Outflow_t = \sum_{c} \left(MS_{t-1,c} - MS_{t,c}\right)$$ *Equation 32*

Table 12 Material intensity by each cohort, functional type, and structure (kg/m²).

		Sand	Gravel	Cement	Brick	Steel	Timber	Lime	Glass
Before 1950									
Industrial	Wood & Brick-wood	732*	245*	112*	855*	0.5	80.9	18*	0.25*
	Brick-concrete	593*	401*	168*	615*	0.9	82.9	40*	2*
Residential	Wood & Brick-wood	732*	245*	112*	855*	0.9	118.1	18*	0.25*
	Brick-concrete	399.2	751.7	307.1	961.7	1.3	66.9	32*	1*
1960-1979									
Industrial	Brick-concrete	508.4	312.5	107.6	849.7	20.3	10.0	28.4	2*
	Reinforced concrete	424.4	346.2	107.3	695.7	20.5	11.0	21.8	2*
Residential	Brick-concrete	382.5	450*	88.0	758.6	11.3	10.0	25.4	2*
	Reinforced concrete	534.6	547.2	186.0	355.6	32.6	20.7	22.4	3.2
1980-1989									
Industrial	Brick-concrete	471.7	428.7	114.8	786.7	16.6	16.1	22.9	2.6
	Reinforced concrete	698.8	619.1	193.4	510.9	47.3	31.9	50.5	3.7
Residential	Brick-concrete	640.7	452.2	144.0	836.7	22.8	17.9	34.4	3.3
	Reinforced concrete	534.6	547.2	186.0	355.6	32.6	20.7	22.4	3.2
1990-1999									
Industrial	Brick-concrete	471.7	428.7	114.8	786.7	16.6	16.1	22.9	2.6
	Reinforced concrete	698.8	619.1	233.0	510.9	66.1	23.3	50.5	3.7
Residential	Brick-concrete	669.3	383.5	155.1	836.3	19.6	17.0	36.7	3.4
	Reinforced concrete	423.4	446.0	147.5	117.4	19.2	20.4	22.5	3.4
Commercial	Brick-concrete	699.3	404.5	167.1	748.5	26.3	17.6	31.5	3.7

	Reinforced concrete	640.8	726.2	297.5	459.4	141.8	27.9	28*	3.7
After 2000									
Industrial	Brick-concrete	471.7	428.7	114.8	786.7	16.6	16.1	22.9	2.6
	Reinforced concrete	698.8	619.1	233.0	510.9	66.1	23.3	50.5	3.7
Residential	Brick-concrete	521.1	363.9	152.4	554.0	23.2	13.7	30.0	4.8
	Reinforced concrete	390.1	455.8	215.7	132.9	59.0	18.2	37.6	4.0
Commercial	Brick-concrete	748.5	178.5	168.4	426.1	31.4	33.6	47.0	7.6
	Reinforced concrete	577.3	341.0	278.7	179.3	70.3	33.6	65.9	7.6

6.3 Results

6.3.1 Urban landscape change

The Tiexi district underwent two distinct phases of urban metabolism. The first one was industry-focused, spanning nearly a century from 1910-1997, and a second phase from 2002 is focusing on residence and commerce (*Figure 29*).

Evolution and change in the district in the first phase were sluggish and haphazard. Throughout the first phase the number of industrial buildings, mostly manufacturing and warehouses (Xiong 2017), kept growing, peaking at 1,889 buildings in 1997. Residential buildings, simple low-rise workers' dormitories, were slowly added mostly in the north of the industrial zone, and roads were developed to support the transportation of materials and products. Spatially, prior to the 1960s, building dispersion was clustered across the district and gradually expanded towards the district's boundaries. Subsequently, new construction densified the district until near-saturation of the available space, giving rise to an unorganized and seemingly organic urban pattern. Building sizes varied considerably. Buildings occupied 2.3% of the land area in 1910, growing to 34.1% of the land area in 1997, and floor area increased by a factor of 21 from 0.38 km^2 to 7.98 km^2, though the average number of floors only increased from 1.7 stories to 2.3 stories during these 87 years, keeping Tiexi a low-rise zone.

The second urban metabolic phase witnessed the complete redevelopment of the district. The turning point took place in 2002 when the decision to revitalize the old industrial zone was implemented. Within about 15 years, the vast majority of industrial buildings vanished, their companies either shut down or relocated. They were replaced by a high-density high-rise residential community accompanied by commercial and public buildings, and by 2018 only a handful of clutches of industrial buildings remain. There are now seven times more residential buildings than industrial buildings. Unlike the previous phase, new construction was conducted in blocks, resulting in a highly ordered urban structure with clearly planned hierarchical patterns. Total floor area doubled to 19.5 km^2, yet the overall footprint shrunk a little to 2.66 km^2, and Tiexi is now a high-rise area with average number of stories of 7.3.

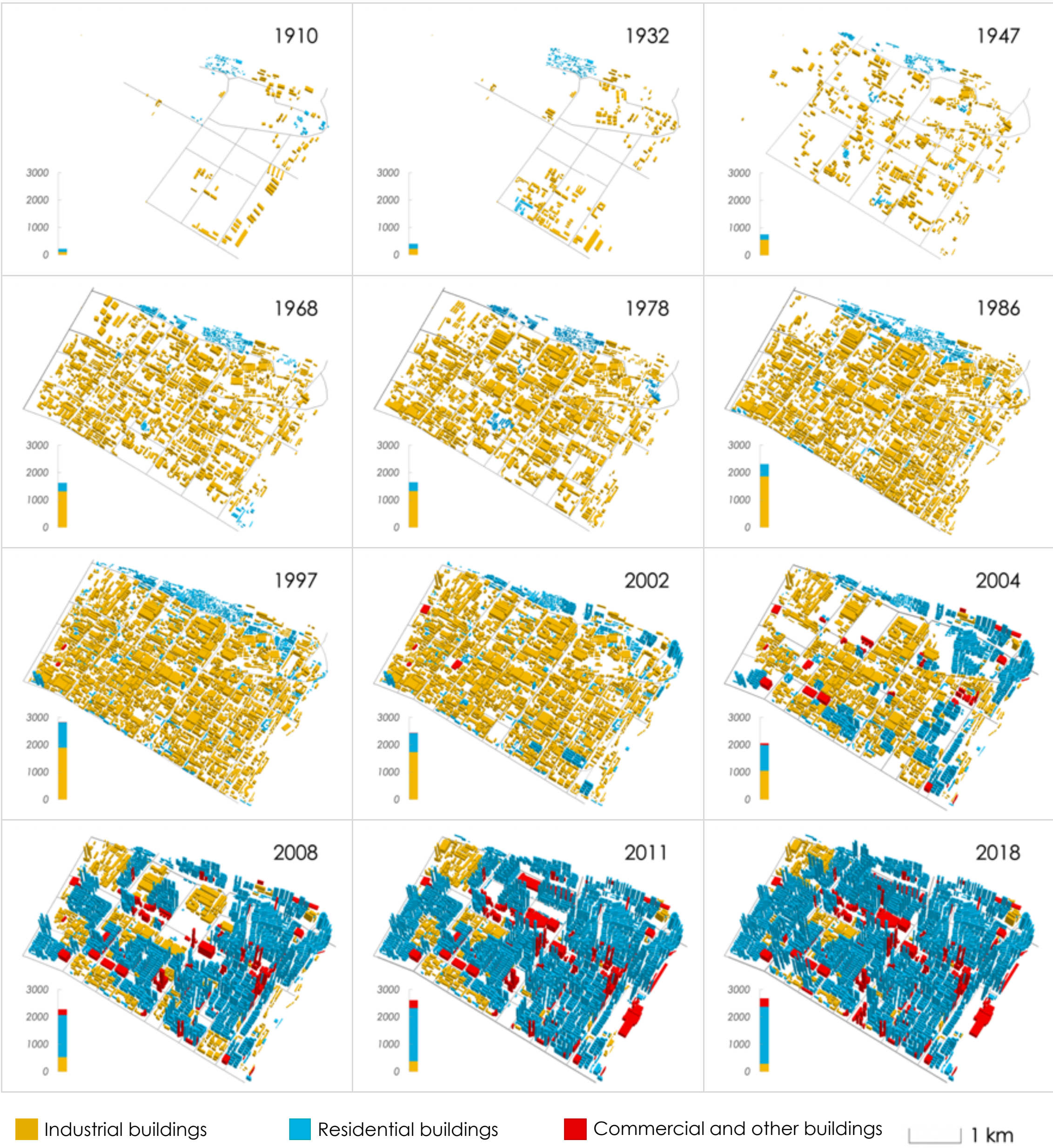


Figure 29 The evolution of the urban form of the Tiexi district, 1910-2018.

The bars show the number of buildings by functional type. See the supporting information for high resolution reproductions of these panels.

6.3.2 Building material stock and flows over time

The Tiexi district's building material stock was 0.76 Tg (teragrams, million tonnes) at the beginning of twentieth century and gradually accumulated to 3.09 Tg in 1947 with an average annual increment of 0.06 Tg (Figure 30a). In the following half century, a relatively steady average annual net addition of 0.13 Tg brought material stock to 8 Tg in 1997. Between 1997 and 2004 the total mass of material stock was virtually constant, obscuring the rapid changes that occurred in its composition during this time and the inflows and outflows that corresponded to these changes. Material stock growth resumed in 2004 and material stocks doubled in the last 15 years. Throughout most of the district's history, the vast majority of materials were stocked in industrial buildings, but the material stock of residential buildings surpassed industrial ones after 2004. The total mass of residential buildings is 20.5 Tg (78%) and commercial, official and other public facilities hold another 3.47 Tg materials (13%) in 2018.

The composition of the stock was dominated by brick for most of the history of Tiexi, accounting for around 35% of total building stock, though it declined to only 17% by 2018 (Figure 30b). At present, sand, gravel, and cement - primary materials for concrete and mortar - compose 74% of the stock, up from only half a hundred years ago. This change is attributed to the shift in the dominant construction method from brick concrete to reinforced concrete to meet the requirements of high-rise buildings. Steel has also been used more for stronger building frames. The other materials (lime, timber, and glass) only make up 4-5% of all material stock throughout.

In general, material inflows seemingly experienced two peaks during 1947-1968 and 2004-2008 (Figure 30c), though the first peak, related to vigorous construction of Tiexi's post-war industrial base, is partly an artifact of the long interval between earlier cohorts in our data. The second peak is the result of the revitalization strategy and urban renewal. In Total, 42Tg of construction materials were input throughout the hundred years, 17 Tg prior to 1997 and the other 57% occurred in the last two decades. Material outflows were relatively low and do not have great fluctuations until 2002, when major demolition began. Between 1910 and 2018, 18 Tg of material outflows were generated yet 90% of them took place during 2002-2018. Therefore, yearly inflow and outflow became more intensive in recent two decades than before.

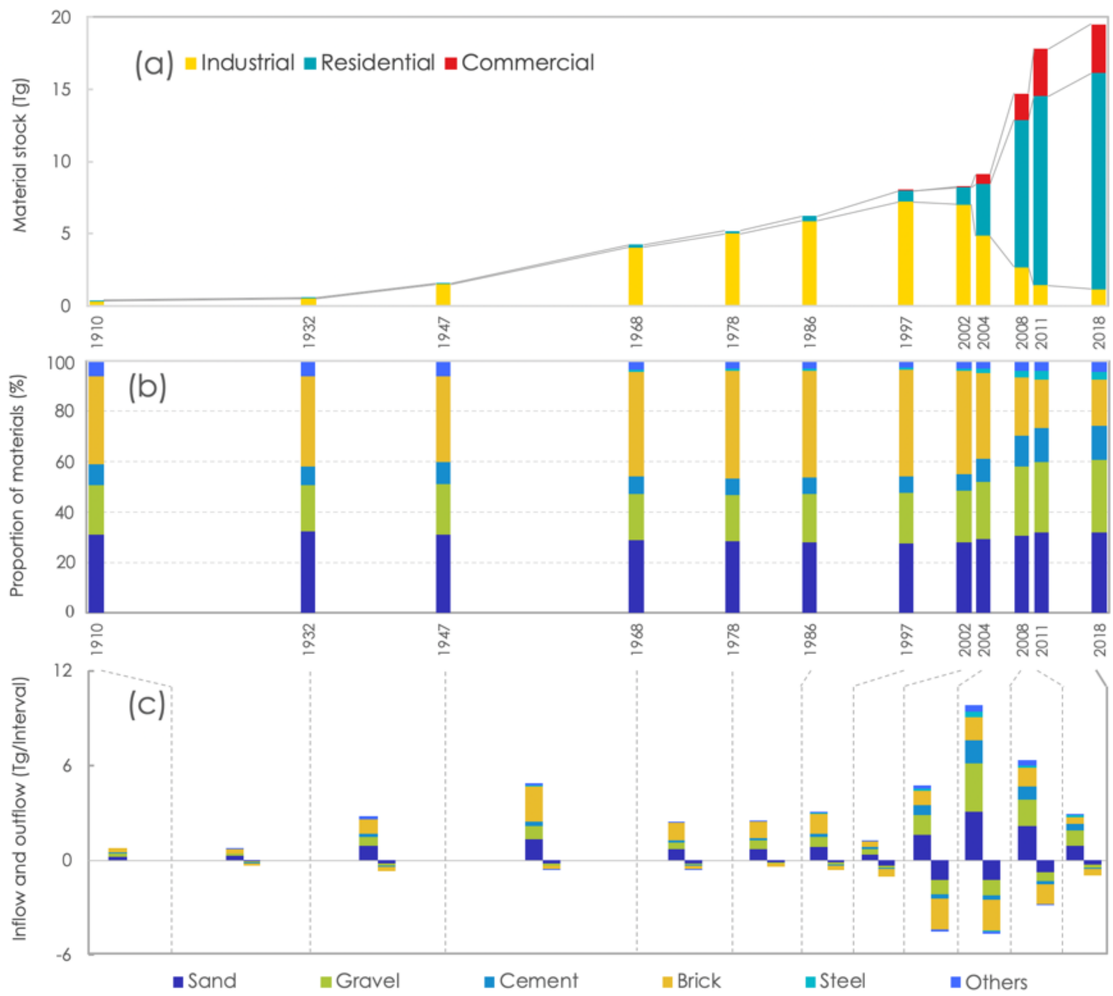


Figure 30 Material stock and flows in the Tiexi district, 1910-2018. (a) Total material stock by functional type; (b) Mass proportion of each type of material; (c) Inflow and outflow by materials in each interval.

The total material inflow is larger than the outflow in most intervals. From a perspective of potential circular use, outflows could not have satisfied new construction consumption even if they were entirely reused and recycled. Even in the intervals of 1997-2002 and 2002-2004 in which the inflow and outflow look balanced in total mass, the composition and amount of each material inflow is not matched by the corresponding outflow. Overall, inflows of every material category were constantly higher than outflows in the same period, except for brick in the latter intervals.

6.3.3 Speeding metabolism

The number of buildings peaked in 1997 with 2825 buildings, then experienced a sharp drop in the following years, especially during 2002-2004 as mass demolition was carried out under the urban renewal strategy (Figure 31a). Building numbers rose again from then to 2011 and subsequently possibly entered a stationary period. Throughout the district's history, young buildings (the two most recent cohorts at any given time) composed around half of the stock because of either substantial new constructions or slow retirement of old cohorts. The uncharacteristically small addition between 1968-1978 can be possibly attributed to the Cultural Revolution (1966-1976) across China. Being busy with demolition activities, fewer buildings were added in 1997-2004.

The survival curves of residential and industrial buildings are plotted for all cohorts in Figure 31b-c. The longest-surviving cohorts, as measured by the time passed until half of the cohort's buildings were demolished, are the residential 1910 cohort and industrial and residential 1947 cohorts, whose median lifetimes are 50-70 years. The 1968 cohort was the biggest addition of new buildings, yet these buildings' median lifetime is only about 35 years. Interestingly, the 1978 cohort seems to have been more vulnerable than preceding cohorts, as its survival curve crosses the older ones and drops below them rather fast. In general, a trend of shortening lifespans is evident from one cohort of construction to the next.

The most striking findings are the patterns of the survival curves in 2002-2008, highlighted in grey in Figure 31b-c. The dramatic effects of urban renewal in this period on the lifetimes of buildings is evident: redevelopment of the district resulted in a contraction of building lifetimes to as short as 2-6 years. Over 50% of residential buildings from the 1997 cohort and industrial buildings of the 1997, 2002, and 2004 cohorts were demolished within a decade from their construction. These visualize as a "compression" of the curves with quite steep slopes in that period. Following the period of major transformation of the district, the curves of these older cohorts revert to less steep slopes, suggesting that the remaining buildings will follow a much slower schedule of retirement and demolition from now on.

The survival curves of the two earliest cohorts exhibit sudden drops between 1932 and 1947. Particularly, industrial buildings (which consist the vast majority of buildings in this period) lost over 50% in the 1932-1947 period, and this pattern is evident to a lesser but nevertheless discernible extent for residential buildings. The surviving buildings from the first two cohorts then remained in use with nearly no losses for decades. This sudden drop resembles the pattern we see in 2002-2008, suggesting that an urban transformation event occurred in 1932-1947 too. While the 2002-2008 urban renewal is well documented and clearly visible in *Figure 29*, the 1932-1947 event is not, and without this analysis of the dynamics of cohort survival would have been overlooked. Nevertheless, it is a dramatic urban metabolism transformation in which over half of the material stock experienced a turnover in a short period of about a decade. We hypothesize that the explanation for this turnover is that factories in this area mainly used for the Japanese military during WWII were partially destroyed by the Soviet Union at the end of the war. We surmise that events of sudden drops in cohort survival curves should be attributed to singular events breaking the "natural" pace of demolition, such as major urban renewal, industrial transformations, and disasters.

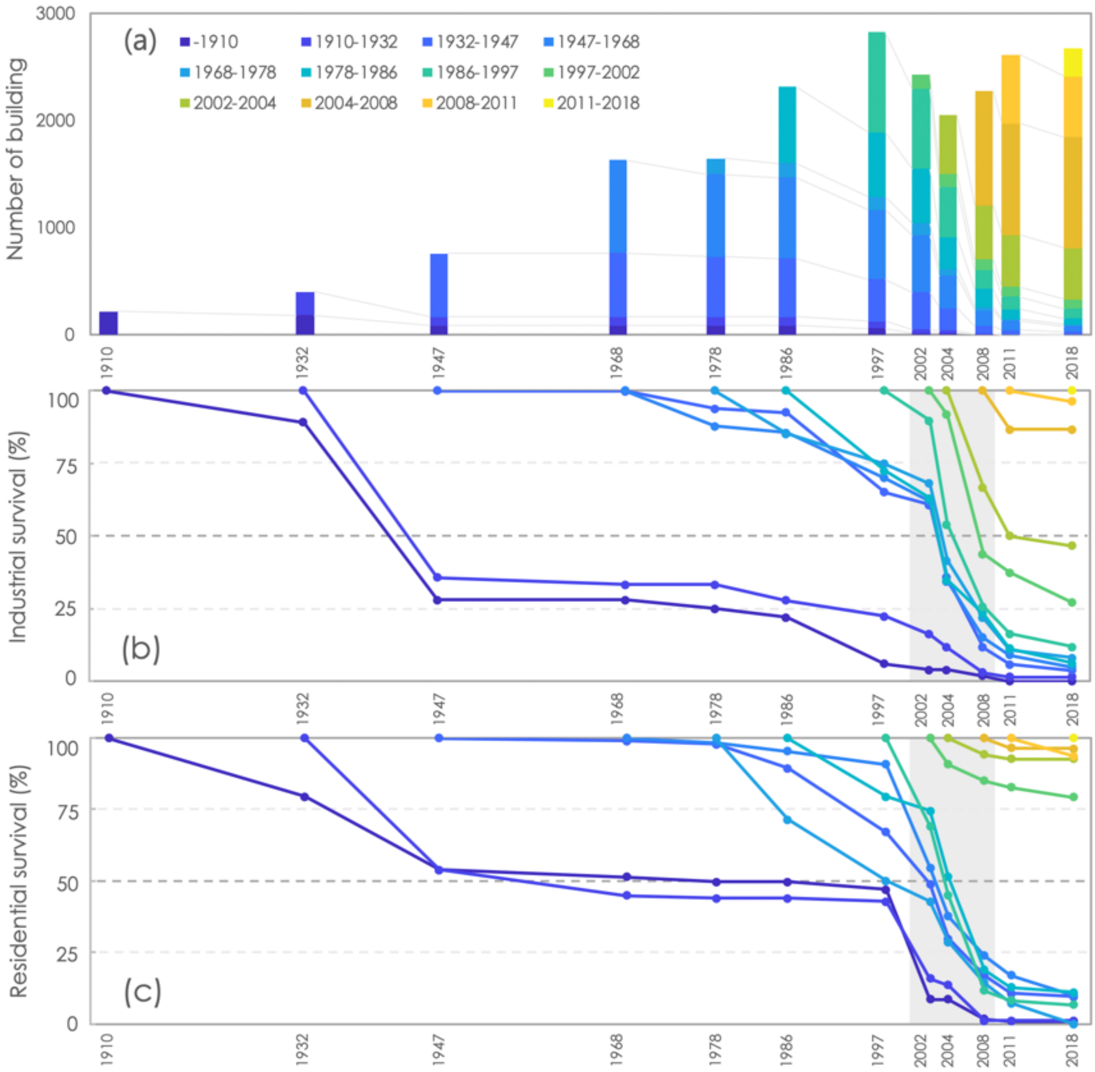


Figure 31 Speed of metabolism in the Tiexi district, 1910-2018.

(a) Total number of buildings by cohorts; (b) Survival rate of industrial building for each cohort; (c) Survival rate of residential building for each cohort.

6.4 Discussion

6.4.1 Opportunities and obstacles for circular material use

No information is available about history of materials recycling in Tiexi though, theoretically, for specific materials high potential for circularity could have been achieved. Detailed comparisons of circularity potentials are included in the supporting information, and here we discuss highlights and setbacks towards their achievement. Sand and gravel outflow could have supplied 70-80% of inflow in the intervals of 1997-2002 and 2002-2004 if those wastes were fully recycled. However, most sand and gravel are embedded in concrete scraps. Crushed concrete can be incorporated into new concrete, albeit with limits as its addition degrades performance, and fresh cement is still required. Although demand for bricks dropped in the redeveloped district, brick stands out with a high ratio of outflow to inflow in recent years, but in practice, used bricks are crushed during demolition, and can be recycled only in the form of aggregate for new concrete rather than the original function. Similarly, the outflow of timber was close to matching inflows in multiple periods, but timber is not usually recycled in structures, basically used for flooring and door or window frames (in the non-structural manner) although it can be retrieved. Nevertheless, in addition to recyclability, economic feasibility is another consideration. For instance, glass is technically recyclable, but retrieving it prior to demolition process is a fragile and time-consuming process, which may cost more than simply purchasing new glass. Steel can technically be recycled with relatively high rates (T. Wang et al. 2015) but materials recycling is not always achieved. The materials that may have a higher technical potential for circular usage, foremost steel, glass, sand, and gravel, have low ratios of outflows to inflows nearly throughout. This highlights the need to consider materials at the building and component scale, waste recyclability, and even the quality of recycled materials beyond a simple mass sum when considering circularity. Early planning and measures for the circularity of demolished waste should be worked out before conducting urban renewal projects, among which is the mapping and quantifying of the resources in buildings.

6.4.2 Rethinking short buildings lifetimes

The survival curves obtained from the results raise points of consideration from both socio-economic analysis perspectives and methodological perspectives. From a socio-economic perspective, the median lifetime of buildings in certain cohorts in our results is less than 10 years, as short as the expected lifespan of electric appliances and shorter than vehicles in many countries. These short lifetimes are not a consequence of physical deterioration or technical problems. Land is state-owned in China (Rougier-Brierre and Jeannet 2009), and the central and local governments therefore play a dominant role in urban policy and design (Qiu 2016; Kamal-chaoui, Leman, and Rufei 2009). This enabled nearly the entire stock of buildings in the Tiexi district to be demolished rapidly due to government strategy which deemed them to be obsolete. Building obsolescence is "a process declining performance resulting in the end of the service life" (Thomsen and Van Der Flier 2011), and those buildings are unlikely to be used anymore and await to be demolished. Following the terminology of Wuyts et al. (Wuyts et al. 2019), we observe that interestingly, while most pre-redevelopment buildings experienced premature obsolescence in comparison to their technical life expectancy, some of the oldest buildings may have survived long after they should have been demolished due to economic difficulties, remaining standing and delipidated until the redevelopment, a kind of delayed obsolescence.

Are such short lifetimes justifiable? From the perspective of material sustainability and efficiency strategies, long lifespans reduce raw material consumption (B. Müller 2006) and slows down demolition waste flows. However, the trade-off is that an older stock may reduce opportunities to embrace new, more energy- and resource-efficient technologies (Hertwich et al. 2019). In practice, it seems that contemporary urban landscapes are changing at an ever-faster pace with faster building turnover and shortening building lifetimes for cohorts of more recently built stock. Our results are in line with empirical evidence from cities or districts in China (Cai et al. 2015), Italy (Miatto et al. 2019), Switzerland (Aksözen, Hassler, and Kohler 2017) which also show such trends. This speeding metabolism of the built environment is increasing environmental impacts and further increases challenges of waste management and resource conservation (Cai et al. 2015; J. Wang, Zhang, and Wang 2018).

On the other hand, the economic and social perspectives of building lifetimes are perhaps overlooked in the resources and environmental literature (Mangold et al. 2016). Shenyang city was faced with a dilemma of empty factories, economic depression, competitiveness loss, and environmental pollution in the Tiexi industrial zone. From the perspective of decision makers, a renaissance of economic growth seemed appealing by shifting from a traditional old manufacturing zone to a modern service industry, and improvement of city livability and attractiveness by replacing factories with a new residential community. International and national awards may corroborate this (M. Wang et al. 2013). As cities intend to stay competitive by attracting investment and revenue-generating inhabitants (Florida 2003), from the view of human well-being in Shenyang, induced mass demolition and the corresponding short lifespans may have been the lesser evil. Of course, policy makers should minimize the environmental impacts when the new strategy or projects are going to design and conduct. Nevertheless, this presents a conundrum between sustainability and development which, without quantification and visualization, may not even earn the attention of decision makers.

From a methodological perspective, the empirical survival curves put into question the common use of survival curves modeled with mathematical functions, usually s-shaped, such as the Weibull and Normal distributions because they do not always fit the empirical observations well. Despite high r^2 values for most fitted curves with both distributions, these curves fail to fully capture the idiosyncrasies of the empirical findings, in particular of the tails of the curves, the shapes of the earliest cohorts, and discrepancies in median lifetimes. Furthermore, the shapes and scales of the empirical curves vary greatly between cohorts, in stark difference to the common assumption of a time-indifferent curve used in many integrated assessment models and dynamic MFA studies. Figure 32 presents a sample of these fitted curves, and further details and fitted parameters are described in the Appendix 5. These findings present a practical challenge, especially for estimating the future schedule of CDW which is required in order to prepare sound waste treatment and circular use capacity.

6.4.3 Implications for urban development and sustainability

China's urbanization processes are ongoing, and urban renewal projects abound across the country, not only in industrial zones but also commonly in older residential districts. Similar processes are occurring throughout the world (Newiger-Addy 2017). In the 20th century and especially after World War II, as the area of cities expanded rapidly in both the USA and Europe (De Sousa 2002), some industrial sites dating from the beginning of the 20th century are to be

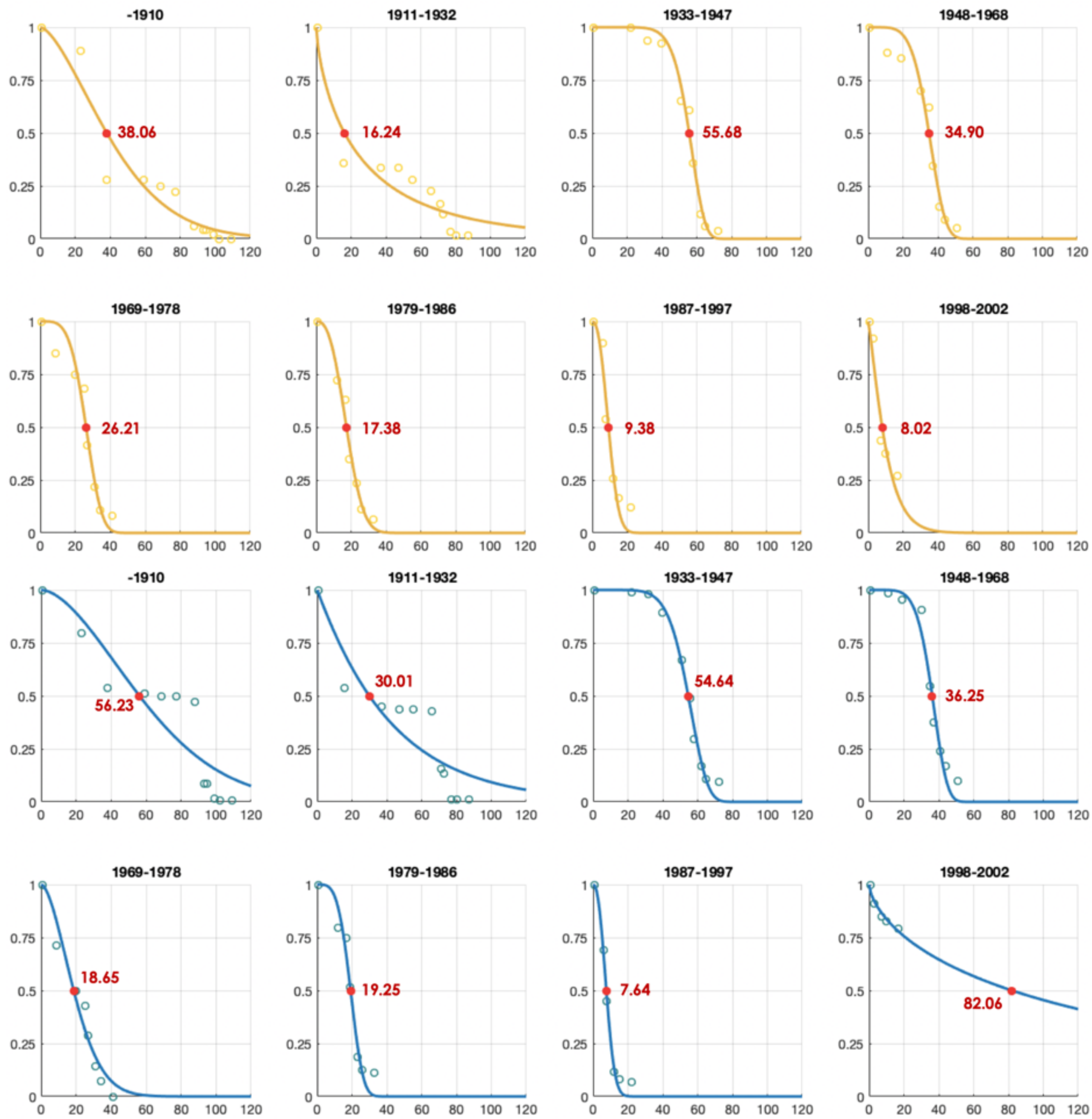


Figure 32 Fitted survival curves for industrial (yellow) and residential (blue) buildings by cohorts modeled with the Weibull distribution.

found in the central areas of cities. In some cases, the old buildings and infrastructure have been included in new plans to retain the historic character of the area; in other cases re-development has brought about a total transformation, making it hard to recognize anything of the historic appearance in the new one (Van Der Toorn Vrijthoff 2006). Tiexi is the latter case of redevelopment. In the last 15 years, the 10 km^2 Tiexi district –about 10% of the city of Paris – has been completely transformed and is considered a socioeconomic success from the decision makers' perspective. Yet our results imply that environmental costs must not be ignored when imitating this model for urban development. There are multiple lessons to learn from the century of urban metabolism history of the Tiexi district.

If making similar plans, the price in terms of construction materials, CDW generation, and related high environmental impacts have to be taken into account. They are also of crucial importance in cost-benefit analysis when assessing and comparing between projects, e.g. redeveloping brownfields versus developing greenfields (De Sousa 2002). A thin line separates between sustainable development and creative destruction – a socially, economically, and environmentally unsustainable policy. Urban metabolism insights call on decision makers to consider long-term overall benefits with the least environmental sacrifice, to avoid repetition of premature obsolescence and reconstruction in short periods of time. Our research brings to light challenges related to the flows of materials over time and the material consequences of short building lifetimes, yet the mapping of existing material stocks can also support planning towards on-site circularity and a market for secondary materials. Using this type of high-resolution, long-term urban material stock and flow data together with advancement of deconstruction/ disassembly for component and material reuse, more adaptable buildings, and modular designs should be promoted and supported, so that they can adapt easily to the next urban transformations, whether intentional or not.

6.4.4 Challenges and opportunities of the 4d-GIS method

The major obstacle of the 4d-GIS method lies in the limited number of maps, aerial photos, and other data, and the differences between the data sources. We discuss data source uncertainty in detail in the supporting information. In our case study, the low availability of records in the early 20th century increases uncertainties, including gaps of information of events between the intervals. However, considering the slow urban metabolic processes and long lifespans of buildings in these periods, we suspect that such omissions are negligible. The empirical survival curves obtained by our method of counting the remaining buildings of a certain cohort in following snapshots are robust even in the relatively long gaps in the early snapshots. Additional snapshots would give further shape to the slopes of the curves but would not change the curves results dramatically because new snapshots cannot affect the values of other snapshots. The use of standardized MI coefficients also involves inherent uncertainties, since buildings are by their nature not standardized and so each building would be expected to have its own unique MI values. We decrease the potential effects of this issue through the use of a relatively diverse set of 24 MIs differentiated by typology, construction period, and construction type. Furthermore, considering the variation and uncertainty of MIs, the results based on average MI values are not interpreted at the scale of individual buildings but rather for the entire Tiexi district, in which the summation reduces variance.

Furthermore, it should be noted that the metabolism of the Tiexi district has not occurred in isolation, but rather as part of greater urban and socioeconomic processes in the city and indeed also at the country and global levels. For instance, material cycling could have occurred and may occur in the future outside the district. Additionally, from the economic development perspective, international companies played an important role in shaping Tiexi in its early days and again in modern times, and so the roles of foreign capital and global economics should be further studied. Although outside the scope and system boundaries of this study, it sets the stage and draws importance to the need to study the interdependences of materials, the environment, the economy, and society at multiple scales.

7. Conclusions

7.1 Summary of the findings

This study presents the evolution and present status on urban building material stock and flows using both dynamic and static bottom-up method with statistical data and GIS data respectively. It claims different challenges and common problems in development and sustainability of urban buildings sector, and discusses how to address the conflict between development and sustainability.

First, the Perpetual Inventory Method (PIM) from the field of economics was adopted for a bottom-up material stock estimation of buildings in 215 Chinese cities from 2000 to 2015. Throughout this period of time, the total construction materials stocked in urban buildings almost tripled, and the net MS addition also kept a constant increase trend with a slight drop in the last two years. Of all, net MS addition to non-residential buildings increased and surpassed residential

MS addition in 2006, followed by a fast growth, implying more construction investment flowed into non-residential buildings to improve the public service and production facilities while ensuring accommodation for the surge of people. The urban building MS in 35 major cities generally accounted for almost half of the total MS. Per capita MS of urban buildings increased from 47.3 tons per person in 2000 to 77.9 tons in 2015. This values in 35 major cities are always higher than rest other cities and such gap has been widen especially in non-residential stock.

Based on buildings material stock estimations of each city, econometric models of panel regression and threshold regression are employed to examine the socioeconomic drivers, especially the impact of urbanization on stock accumulation for cities at the different developing stages. Empirical panel regression shows urbanization positively correlated with urban building MS and overall it explains most of the growth of all models. Relative decoupling of MS accumulation from total population and economic growth seems apparent. The expansion in total population tends to weakly drive the residential building MS, the structure transformation from rural population to urban residents would be the main demand of the non-residential building MS constructions for working, education, health care and other services to improve the living quality and citizen well-being. An increasing number of urban populations effects strongly on those materials accounting for a large proportion, while economic development is more likely to change the material composition, using more steel and cement for new constructions due to more high buildings emerging in cities.

The threshold regression model is used to examine the non-linear effects of urbanization on material stock accumulation under different economic development levels. The effect of urbanization on material stock is proven significantly different under different economic development levels. In economically underdeveloped areas or stage, more construction materials are required for the process of urbanization. When the economy develops to a certain extent and there has been a certain amount of capital accumulation, the elasticity of urbanization on stocks would decrease. Regarding the functional types, as cities grow toward the advanced stage, urbanization still has demand on residential MS but may not for more non-residential part. Generally speaking, the marginal construction material accumulation of urbanization can reduce as economic grows. This draws out a discussion on resources management for different cities. For those economically underdeveloped cities, long-term urban planning, efficient use of resources, and building designing may be the top priority to reduce the environmental impacts for future necessary city construction. While in the wealthy regions, they may no longer face the problem of urban construction in the future, instead, stock and waste management can be their challenge. Before the relevant policy is formulated, the quantity, composition and spatial distribution of current building material stock is necessary to fully understand and studied.

Therefore, the building MS for the 14 wealthy cities of Eastern China was calculated with GIS-based static bottom-up method, showing that in 2017 the building stock of these metropoles reached and even surpassed the MS of cities from developed countries. In total, 7.9 Gt materials are stored in a total area of 3,790 km^2, resulting in an average density of 2.1 Mt/km^2. A hotspot analysis of the material stock distribution was performed, identifying and providing maps of the clusters and location of the MS which are more likely to produce large quantities of CDW and demanding more materials in case of maintenance and retrofitting. The per capita building MS is positively correlated with per capita GDP, informing developed cities should focus on reuse and recycling strategies regarding CDW, while policy makers from still-developing cities should take into account the environmental impacts related to economic growth, whis is consistent with above empirical regression results.

To better investigate the impact of socio-economic development on construction material flow and stock trends and find how to tackle conflicts between development and sustainability, building-by-building the material flows and stock accumulations was chronicled in high-resolution 4d-GIS database for the Tiexi district of Shenyang, a microcosm of China's urban transformations since the early 20th century. 42 million tonnes of construction materials were needed to develop the Tiexi district from 1910 to 2018, and 18 million tonnes of material outflows were generated by end-of-life building demolition. However, over 55% of inflows and 93% of outflows occurred since 2002 during a complete redevelopment of the district. Only small portions of end-of-life materials could have been reused or recycled because of temporal and typological mismatches of supply and demand and technical limitations. Our analysis reveals a dramatic decrease in median building lifetimes to as low as 6 years in the early 21st century. These findings contributing to the discussion of long-term environmental efficiency and sustainability of societal development through construction, and reflect on the challenges of urban renewal processes not only in China, but also in other developing and developed countries that lost (or may lose) their traditional economic base and restructure their urban forms.

7.2 Implications for development and sustainability

China is the country with the largest number of new constructions in the world each year – 2.7 billion square meters of new construction area - equivalent to 40% of the world's cement and steel consumption. This study also confirms that building material stock has increased rapidly since 2000, and driven by socio-economic factors especially urbanization. To support the constant urbanization, it is foreseeable that a large amount of construction materials will be required in the future. Facing the inevitable trend of social development, how to reduce its environmental impact as much as possible to achieve sustainability becomes the focus construction sector and local governments.

The empirical results of threshold regression show that the impact of urbanization on material stocks is relatively small in areas with a high level of economic development. From the perspective of reducing material stocks, the more rural population should move to cities with high economic development levels in future urbanization of China. The past experience also witnessed population tends to migrate to economically developed regions. However, this will trigger other social issues, like overburden for mega cities, uneven regional development, etc. Urbanization and city construction are also necessary for median and small cities, that is rebalance growth away from mega cities to smaller cities. And it is worth noting that urbanization requires more non-residential buildings MS according to the empirical regression model. Non-residential buildings are more complex in architectural structure and materials use, therefore, both pre-construction and post-waste-disposal require more research and attention than residential buildings. Those findings provide fundamental information for National New-type Urbanization Plan (NUP) proposed in March 2014 and coming 14^{th} five-year plan of China.

The growing stock of buildings is usually considered as useful constructions for increasing demand of the urban population, however, some constructions might not be necessary which we should avoid to reduce the materials input and demolition waste. China's construction industry has always been characterized by large-scale construction and demolition, which not only wastes construction resources, but also makes buildings very short-lived. In addition to physical factors such as building quality, some social and economic factors, such as planning, are key reasons. At present, China is in an era of planning explosion. Urban planning is said chaotic and not in harmony with the pace of urban development in the future. No matter how good the building quality is, it will be hard to escape the misfortune. In particular, the phenomenon of "one set of urban planning by one government" is common in many cities, resulting in repeating construction and demolition in short term. These unnecessary repetitive construction and dismantling are important obstacles to achieve the sustainable development, and are issues worthy of reflection and attention by the central and local governments. Especially for less-developed regions, long-term and careful decision-making is required in future planning. This may involve the government, financial system, land policy, etc., beyond the scope of this study, but this study provides a theoretical and empirical basis for policy research.

As the economy develops, the urban metabolism is speeding up from empirical study of Tiexi, which is consistent with other existing research. Thus, a huge amount of demolition waste is generated. Whether it is a mega city that has accumulated a lot of materials, or a small and medium-sized city that is undergoing rapid developing, it is urgent to improve the utilization of CDW in this country. Research and practices show that CDW can be used as an urban mineral resource. Concrete, mortar, bricks and tiles in CDW can be recycled into aggregates and other recycled materials through a certain process, which can be used for pavement base, recycled concrete and related products, and various types of permeable materials in the construction of sponge cities to achieve effective waste utilization. On the one hand, it can reduce a series of pollution problems caused by CDW, on the other hand, it can substitute natural raw materials for building materials production, reduce virgin resource consumption, which is significantly beneficial for both society and environment, and is an inevitable choice for urban sustainable development. The material stock estimation in this study informs governments and enterprises the amount, composition, and location of potential wastes to make further decisions. In addition, if a large amount of waste generated in large cities is considered from perspective of regional management, its recycling may provide materials for the construction of neighboring small and medium-sized cities. This requires further research with consideration of economic feasibility.

Government plays a very important role in determining the policy and promoting its implementation, especially in China. It is responsible for environmental issues of construction sector, but also powerful to tackle them and make a difference for our living environment. As a populous country, China's performance toward the sustainable development would influence the progress of the whole world.

7.3 Limitation of research and future directions

This study focuses on the major construction materials stocked in Chinese buildings at city level and their evolution patterns along with socioeconomic development. Although great efforts have been made for filling gaps in terms of study scales, estimation models, linkages between the physical material stock and socio-economic development, there are several issues were ignored here. The study did not include the underground part of building as it increases collection difficulty for both statistical GIS data. Material flows of maintenance and renovation were out of my scope, which might influence the final results especially for 4d-GIS material stock and flow estimations. This study greatly improves the database of material intensity for Chinese building by fitting distribution functions for different structures of buildings, but the difference among cohorts could not be derived due to the limited samples, which also might have impact on final stock and flow estimations. Moreover, this study only reviewed the past patterns and changes in material stock and flow at city level, further forecasting is necessary to answer how much construction material will be required and how much demolition waste will be generated for next 50 or 100 years as the urbanization proceeds under different strategy scenarios.

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Figure list

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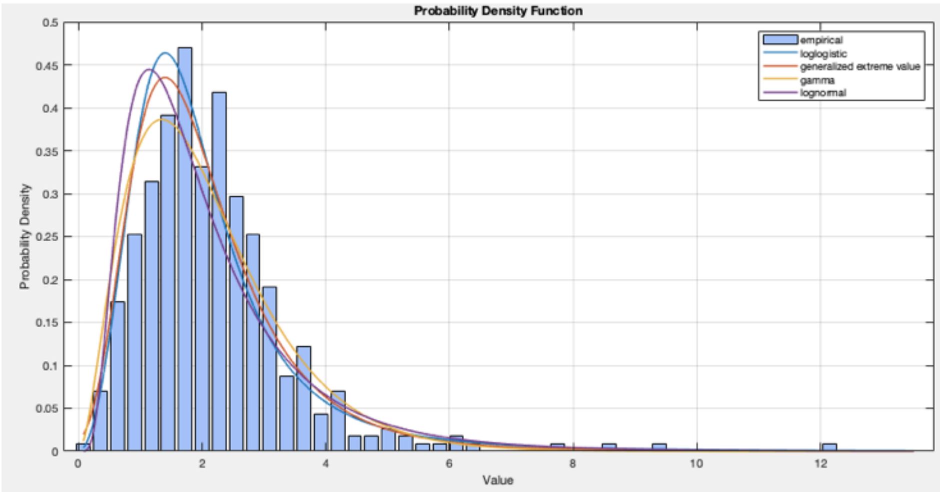
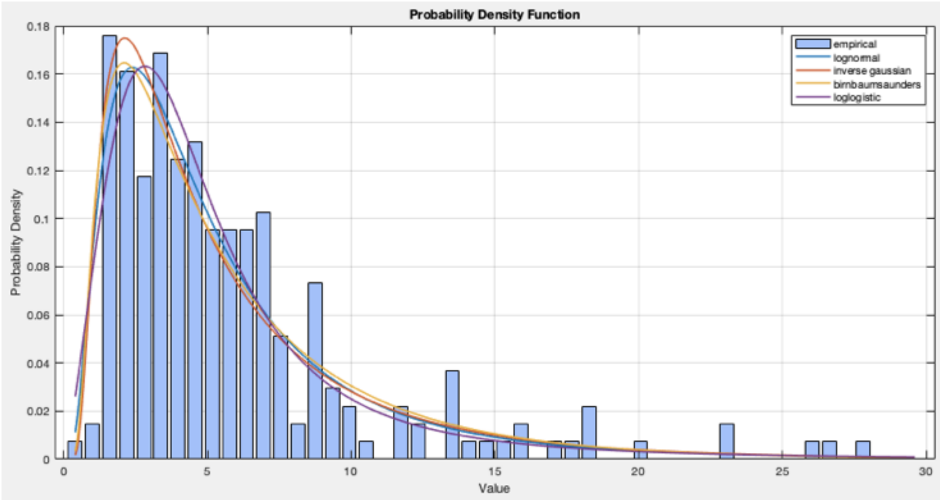
Appendix

Appendix 1. Material intensity fitting curves and parameters



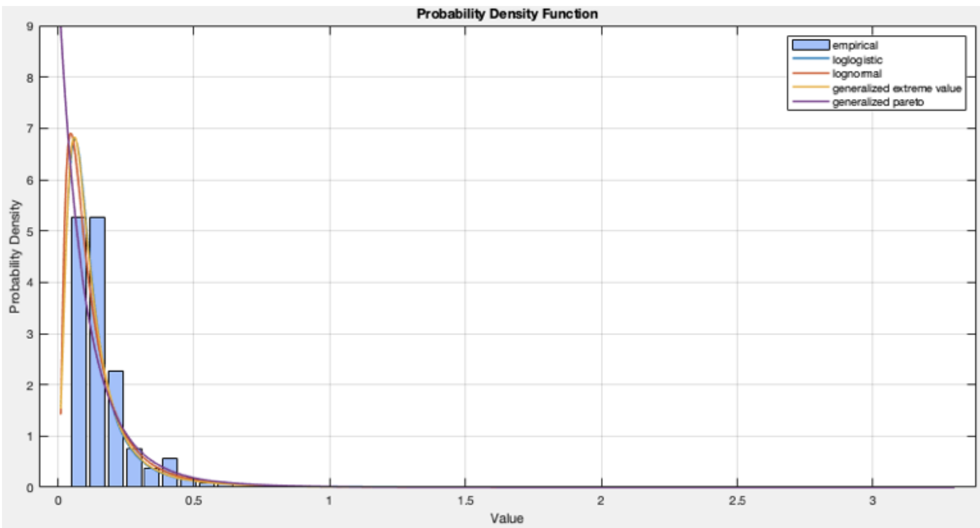
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	loglogistic	generalized extreme value	gamma	lognormal
NLogL	619.69	616.6977	627.837	636.1218
BIC	1251.4606	1251.5162	1267.7545	1284.3241
AIC	1243.3801	1239.3954	1259.674	1276.2436
AICc	1243.4089	1239.4531	1259.7028	1276.2723
Params Nemas	mu, sigma,	k, sigma, mu,	a, b,	mu, sigma,
Params Values	0.57804 0.34029	0.10438 0.84953 ...	2.8511 0.72582	0.54177 0.64086

(1) Histogram of steel intensity for BC structure, fitting curves and parameters



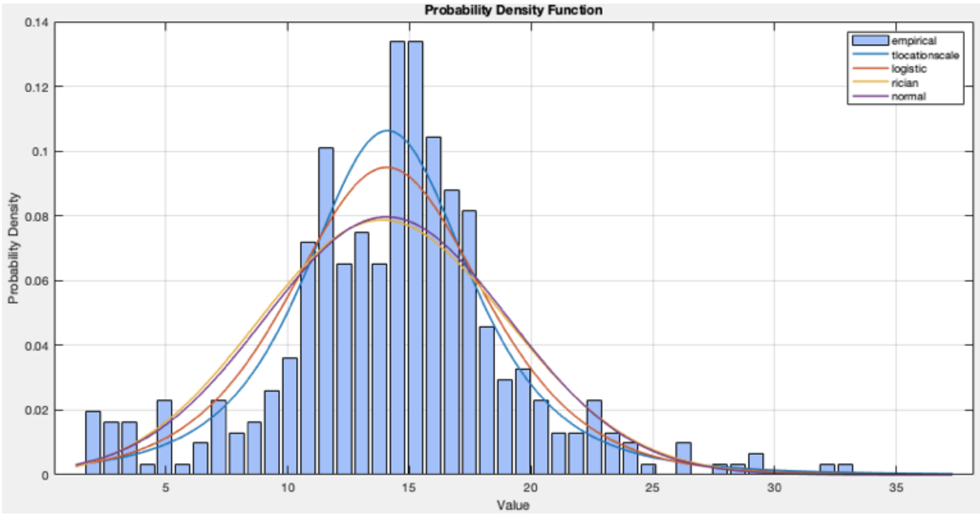
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	lognormal	inverse gaussian	birnbaumsaunders	loglogistic
NLogL	599.1901	599.304	599.6682	602.0326
BIC	1209.2564	1209.4842	1210.2125	1214.9413
AIC	1202.3802	1202.608	1203.3363	1208.0652
AICc	1202.4331	1202.6609	1203.3892	1208.118
Params Nemas	mu, sigma,	mu, lambda,	beta, gamma,	mu, sigma,
Params Values	1.4581 0.7636	5.7679 7.3958	4.3282 0.81746	1.4511 0.43744

(2) Histogram of steel intensity for SC structure, fitting curves and parameters



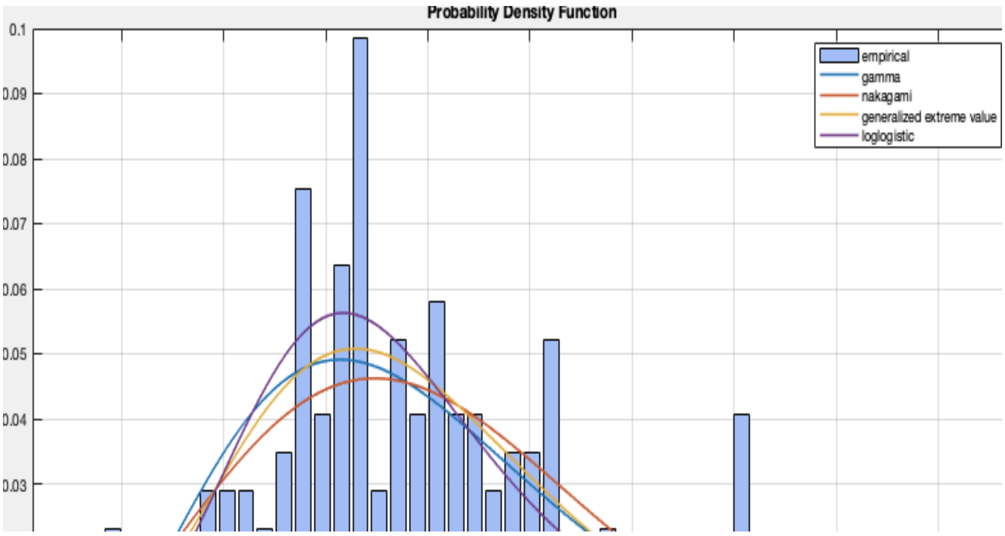
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	loglogistic	lognormal	generalized extreme value	generalized pareto
NLogL	-173.089	-169.6418	-172.0259	-165.1972
BIC	-336.0402	-329.1457	-328.8451	-315.1876
AIC	-342.178	-335.2835	-338.0518	-324.3943
AICc	-342.1011	-335.2066	-337.897	-324.2395
Params Nemas	mu, sigma,	mu, sigma,	k, sigma, mu,	k, sigma, theta,
Params Values	-2.3159 0.46764	-2.333 0.86098	0.36067 0.056977 0.075971	0.15546 0.11142 ...

(3) Histogram of steel intensity for BW structure, fitting curves and parameters



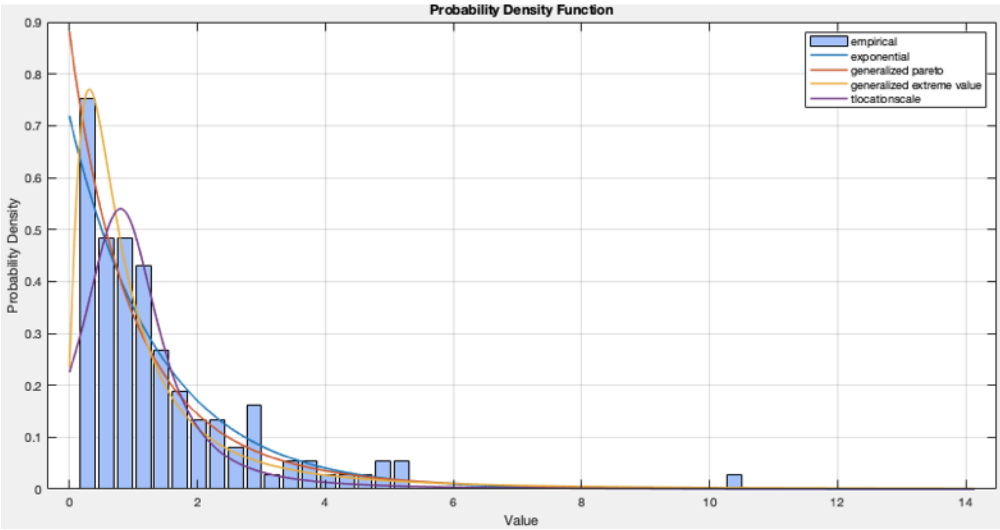
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	tlocationscale	logistic	rician	normal
NLogL	1244.8807	1248.6351	1265.9031	1265.9578
BIC	2507.8678	2509.3411	2543.8771	2543.9866
AIC	2495.7614	2501.2702	2535.8062	2535.9156
AICc	2495.8194	2501.2991	2535.8351	2535.9445
Params Nemas	mu, sigma, nu,	mu, sigma,	s, sigma,	mu, sigma,
Params Values	14.0981 3.49139 ...	14.065 2.63267	12.926 5.27536	14.0616 5.00714

(4) Histogram of cement intensity for BC structure, fitting curves and parameters



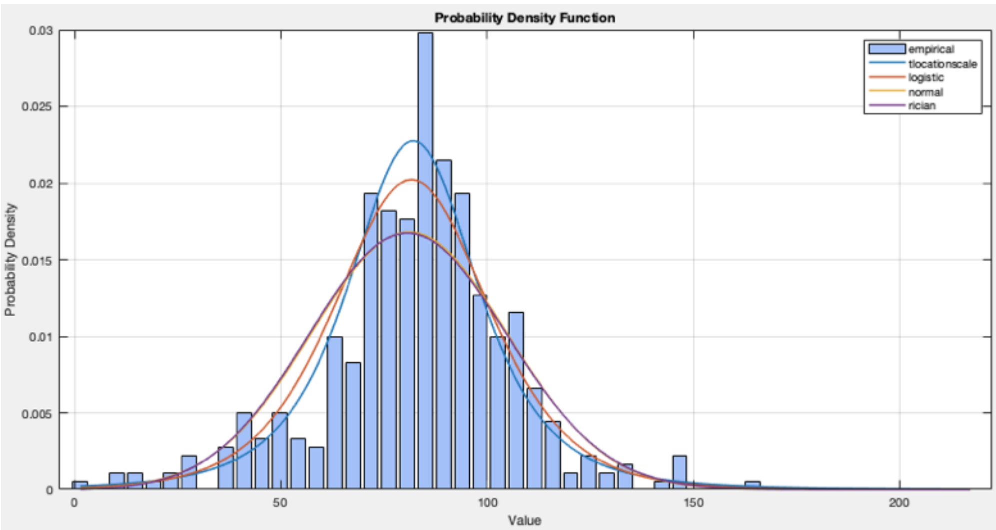
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	gamma	nakagami	generalized extreme value	loglogistic
NLogL	661.1077	661.2208	658.9261	662.6111
BIC	1332.6777	1332.9039	1333.5456	1335.6844
AIC	1326.2155	1326.4417	1323.8523	1329.2222
AICc	1326.2807	1326.5069	1323.9834	1329.2874
Params Nemas	a, b,	mu, omega,	k, sigma, mu,	mu, sigma,
Params Values	4.9022 4.0273	1.433919 465.0921	-0.0633949 7.2595...	2.9033 0.26104

(5) Histogram of cement intensity for SC structure, fitting curves and parameters



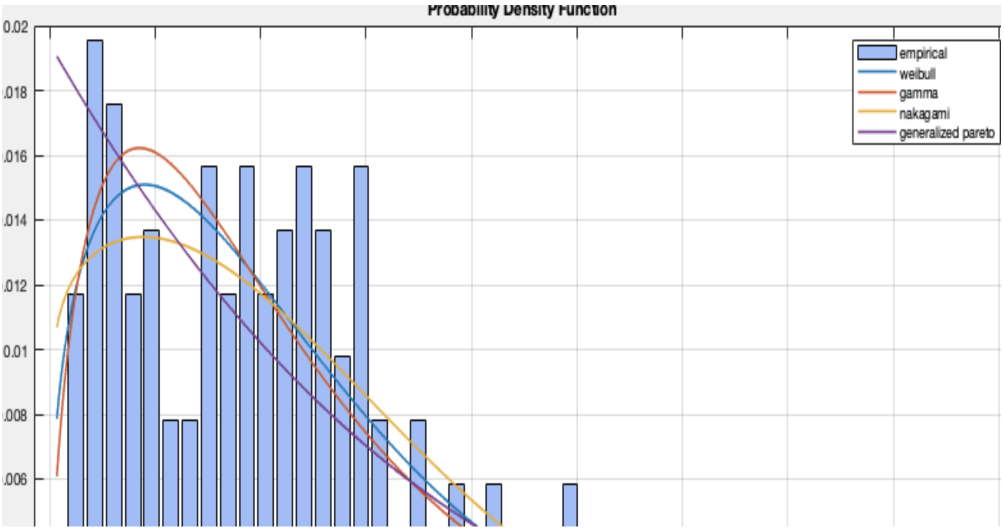
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	exponential	generalized pareto	generalized extreme value	tlocationscale
NLogL	172.8958	169.928	173.9049	209.246
BIC	350.6591	354.4586	362.4125	433.0945
AIC	347.7916	345.856	353.8099	424.4919
AICc	347.8228	346.0465	354.0003	424.6824
Params Nemas	mu,	k, sigma, theta,	k, sigma, mu,	mu, sigma, nu,
Params Values	1.3909	0.18071 1.1348 -2....	0.61601 0.55997 ...	0.80102 0.64233 ...

(6) Histogram of cement intensity for BW structure, fitting curves and parameters



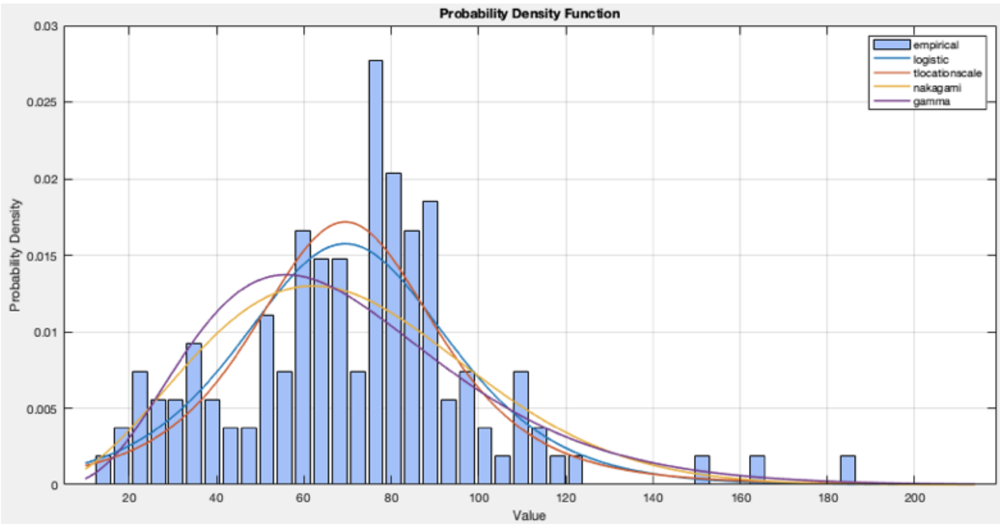
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	tlocationscale	logistic	normal	rician
NLogL	1868.0326	1872.8668	1893.6065	1895.6207
BIC	3754.1355	3757.7806	3799.2598	3803.2883
AIC	3742.0652	3749.7337	3791.2129	3795.2414
AICc	3742.1239	3749.763	3791.2422	3795.2706
Params Nemas	mu, sigma, nu,	mu, sigma,	mu, sigma,	s, sigma,
Params Values	82.0901 16.2995 ...	81.6764 12.3662	81.0869 23.7427	77.1016 24.4212

(7) Histogram of brick intensity for BC structure, fitting curves and parameters



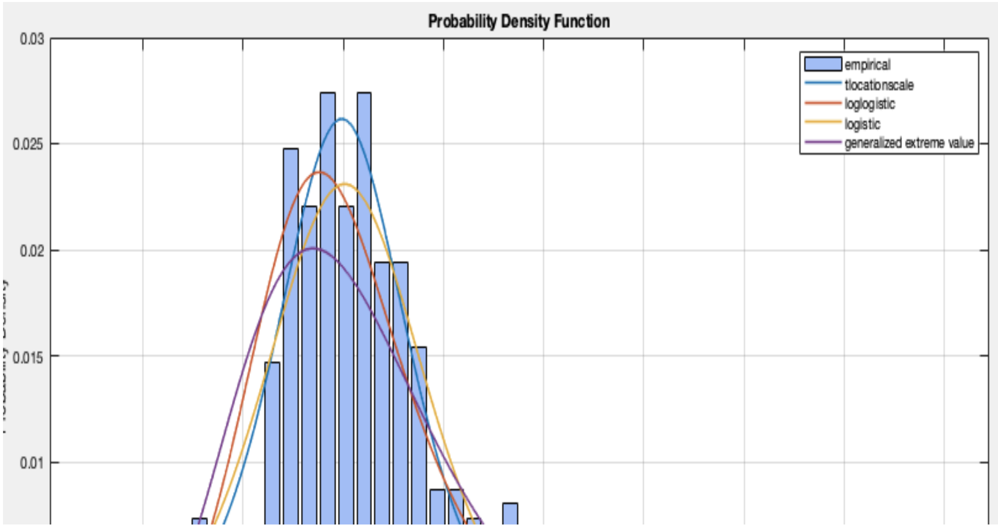
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	weibull	gamma	nakagami	generalized pareto
NLogL	681.4689	682.0169	682.7018	681.9735
BIC	1372.8774	1373.9733	1375.3433	1378.8565
AIC	1366.9378	1368.0337	1369.4037	1369.9471
AICc	1367.0229	1368.1188	1369.4888	1370.1185
Params Nemas	A, B,	a, b,	mu, omega,	k, sigma, theta,
Params Values	48.6433 1.35402	1.6203 27.514	0.55668575 3097....	-0.224344 52.4716...

(8) Histogram of brick intensity for SC structure, fitting curves and parameters



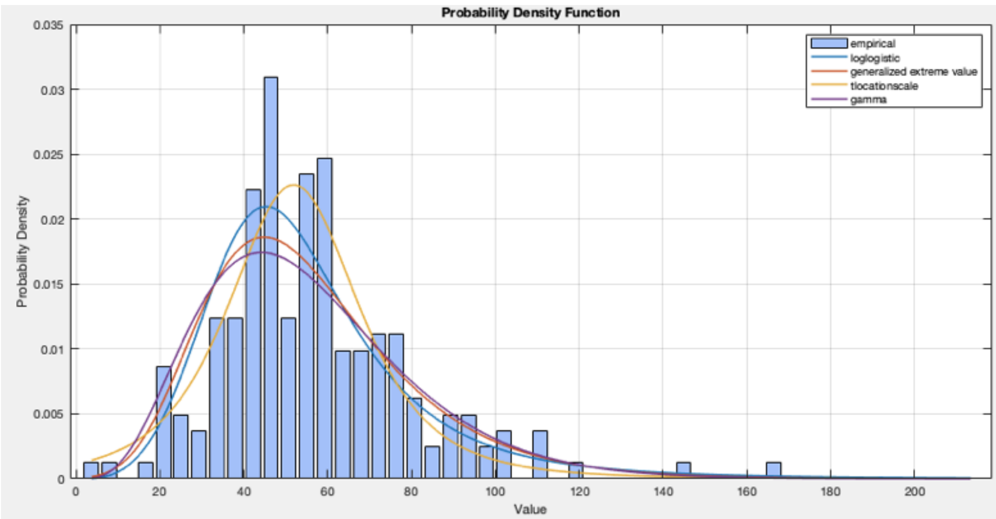
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	logistic	tlocationscale	nakagami	gamma
NLogL	626.4488	624.7939	629.455	630.1511
BIC	1262.6479	1264.2135	1268.6604	1270.0527
AIC	1256.8975	1255.5879	1262.91	1264.3023
AICc	1256.9913	1255.7769	1263.0037	1264.396
Params Nemas	mu, sigma,	mu, sigma, nu,	mu, omega,	a, b,
Params Values	69.454 15.8813	69.4421 21.8168 ...	1.4379132 5899.11...	4.86349 14.4781

(9) Histogram of brick intensity for BW structure, fitting curves and parameters



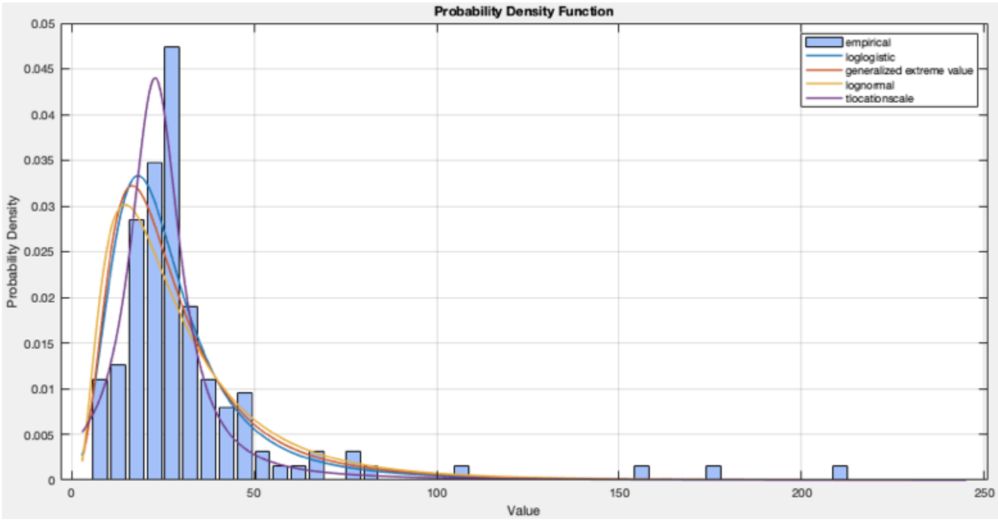
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	tlocationscale	loglogistic	logistic	generalized extreme value
NLogL	1801.3201	1808.2424	1810.5899	1818.6866
BIC	3620.696	3628.5219	3633.2169	3655.4289
AIC	3608.6403	3620.4848	3625.1797	3643.3731
AICc	3608.6992	3620.5142	3625.2091	3643.4321
Params Nemas	mu, sigma, nu,	mu, sigma,	mu, sigma,	k, sigma, mu,
Params Values	59.7284 14.1769 ...	4.0801 0.18491	60.2815 10.825	-0.0672067 18.382...

(10) Histogram of sand intensity for BC structure, fitting curves and parameters



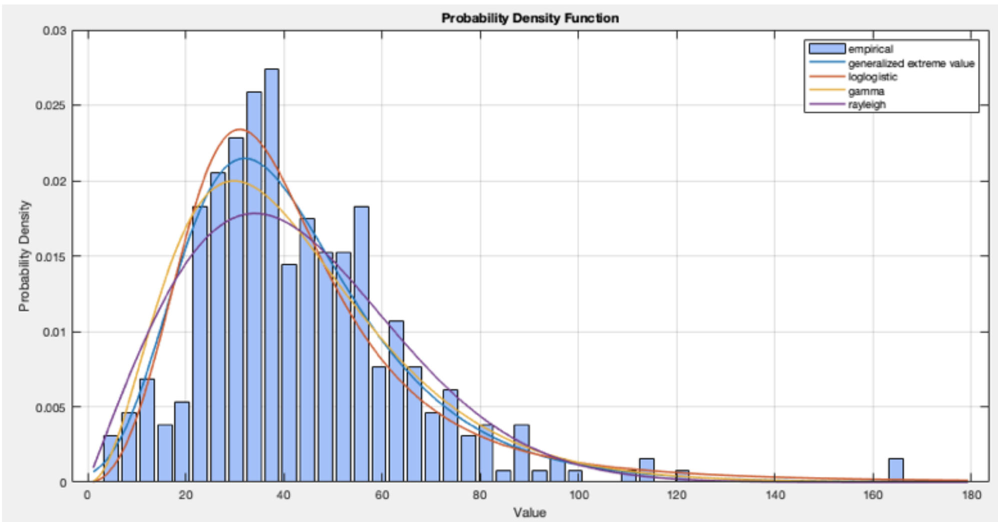
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	loglogistic	generalized extreme value	tlocationscale	gamma
NLogL	862.6492	862.7212	863.2442	868.4437
BIC	1735.7924	1741.1834	1742.2294	1747.3814
AIC	1729.2983	1731.4423	1732.4884	1740.8874
AICc	1729.3625	1731.5714	1732.6174	1740.9515
Params Nemas	mu, sigma,	k, sigma, mu,	mu, sigma, nu,	a, b,
Params Values	3.9383 0.24703	-0.0103468 19.77...	51.8735 16.3138 ...	4.89122 11.3567

(11) Histogram of sand intensity for SC structure, fitting curves and parameters



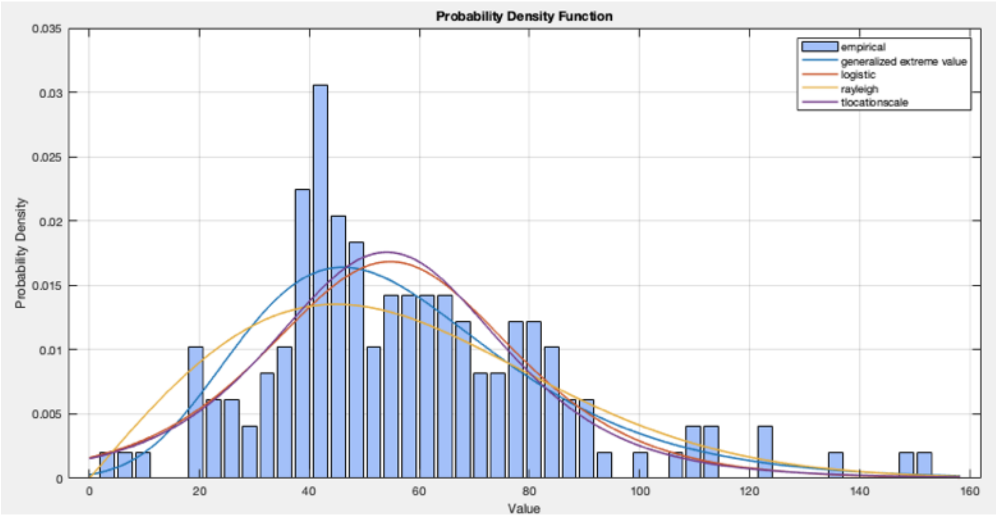
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	loglogistic	generalized extreme value	lognormal	tlocationscale
NLogL	540.4974	542.9861	547.8809	547.9248
BIC	1090.7144	1100.5517	1105.4814	1110.4291
AIC	1084.9947	1091.9722	1099.7618	1101.8497
AICc	1085.09	1092.1642	1099.857	1102.0417
Params Nemas	mu, sigma,	k, sigma, mu,	mu, sigma,	mu, sigma, nu,
Params Values	3.1706 0.35962	0.278228 11.8331 ...	3.1807 0.70568	22.8412 7.64533 ...

(12) Histogram of sand intensity for BW structure, fitting curves and parameters



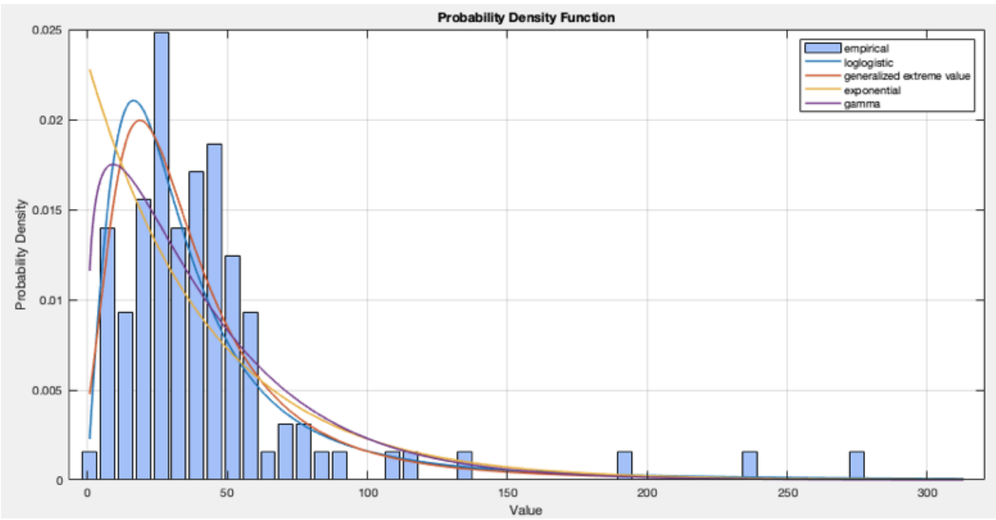
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	generalized extreme value	loglogistic	gamma	rayleigh
NLogL	1599.9811	1609.452	1609.8623	1616.596
BIC	3217.6372	3230.6873	3231.5078	3239.0837
AIC	3205.9623	3222.904	3223.7245	3235.192
AICc	3206.0293	3222.9374	3223.7579	3235.2031
Params Nemas	k, sigma, mu,	mu, sigma,	a, b,	B,
Params Values	0.0160511 17.1298...	3.6339 0.31153	3.38695 12.48	34.0381

(13) Histogram of gravel intensity for BC structure, fitting curves and parameters



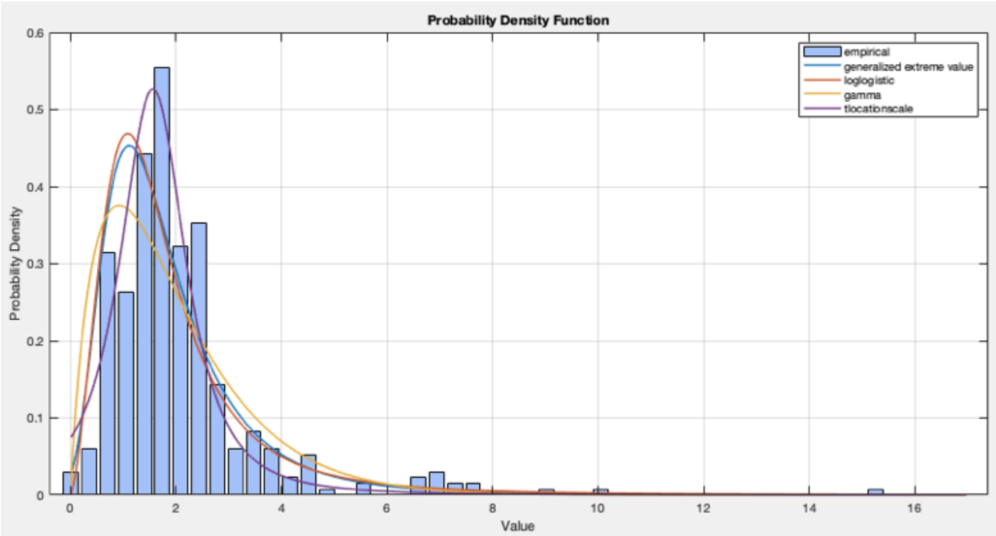
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	generalized extreme value	logistic	rayleigh	tlocationscale
NLogL	713.2676	719.9018	723.3588	719.3527
BIC	1441.6266	1449.8646	1451.7479	1453.7967
AIC	1432.5353	1443.8037	1448.7175	1444.7054
AICc	1432.6964	1443.8837	1448.744	1444.8664
Params Nemas	k, sigma, mu,	mu, sigma,	B,	mu, sigma, nu,
Params Values	-0.041185 22.4466...	54.6906 14.8481	44.8313	54.0637 21.5791 ...

(14) Histogram of gravel intensity for SC structure, fitting curves and parameters



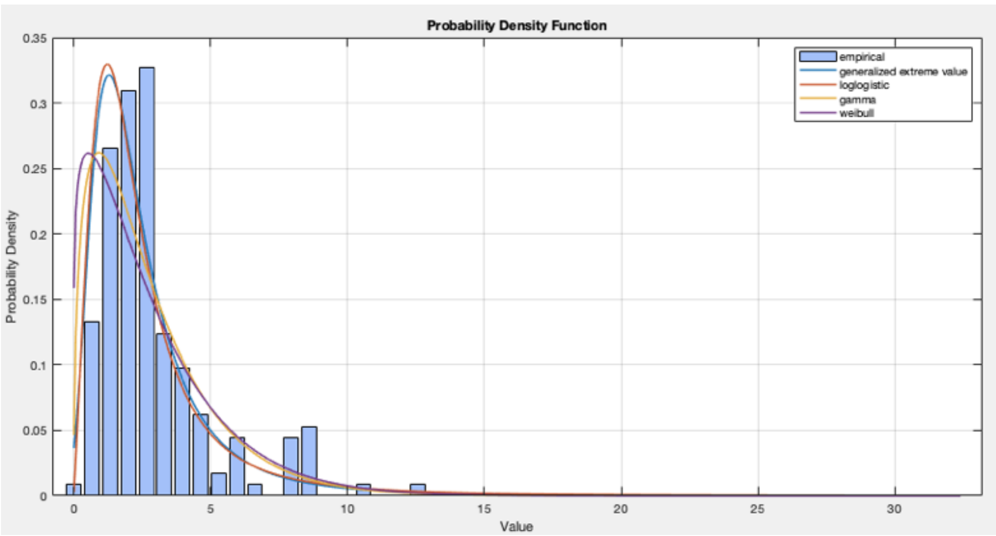
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	loglogistic	generalized extreme value	exponential	gamma
NLogL	480.8578	479.2636	485.9573	484.2967
BIC	970.9656	972.4021	976.5395	977.8434
AIC	965.7156	964.5271	973.9145	972.5934
AICc	965.8368	964.772	973.9545	972.7146
Params Nemas	mu, sigma,	k, sigma, mu,	mu,	a, b,
Params Values	3.4092 0.52437	0.293259 19.1755 ...	43.1329	1.26707 34.0414

(15) Histogram of gravel intensity for BW structure, fitting curves and parameters



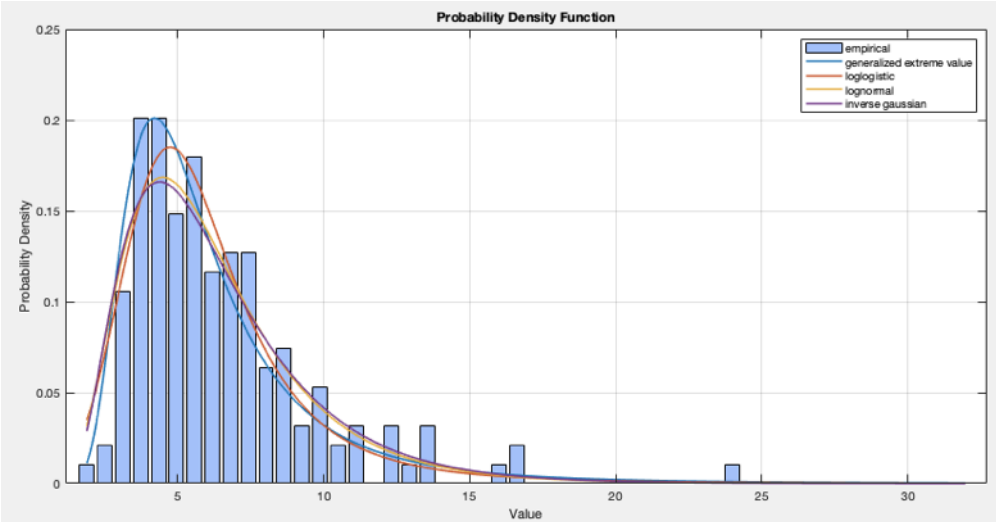
	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	generalized extreme value	loglogistic	gamma	tlocationscale
NLogL	576.6107	588.2316	603.655	602.0326
BIC	1171.0889	1188.3749	1219.2218	1221.9326
AIC	1159.2214	1180.4632	1211.3101	1210.0651
AICc	1159.2842	1180.4946	1211.3414	1210.128
Params Nemas	k, sigma, mu,	mu, sigma,	a, b,	mu, sigma, nu,
Params Values	0.1913 0.82641 ...	0.43738 0.40911	1.9014 1.0232	1.5616 0.67171 ...

(16) Histogram of wood intensity for BC structure, fitting curves and parameters



	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	generalized extreme value	loglogistic	gamma	weibull
NLogL	329.5658	332.2097	339.8075	343.6502
BIC	674.574	674.7144	689.91	697.5954
AIC	665.1316	668.4194	683.615	691.3004
AICc	665.2744	668.4904	683.686	691.3715
Params Nemas	k, sigma, mu,	mu, sigma,	a, b,	A, B,
Params Values	0.2884 1.1889 1...	0.7001 0.47725	1.4908 1.8581	2.9376 1.16

(17) Histogram of wood intensity for SC structure, fitting curves and parameters



	Distribution 1	Distribution 2	Distribution 3	Distribution 4
Dist Name	generalized extreme value	loglogistic	lognormal	inverse gaussian
NLogL	365.9677	369.9707	370.3657	370.6922
BIC	747.0657	750.0282	750.8183	751.4713
AIC	737.9354	743.9413	744.7314	745.3845
AICc	738.0943	744.0203	744.8104	745.4634
Params Nemas	k, sigma, mu,	mu, sigma,	mu, sigma,	mu, lambda,
Params Values	0.25828 1.8869 ...	1.7002 0.265	1.7239 0.47231	6.33987 25.1875

(18) Histogram of wood intensity for BW structure, fitting curves and parameters

Appendix 2. Material stock of urban buildings in 215 cities

The first 35 cities in grey are primary cities discussed in Chapter 4. Unit: million tons

No.	Province	City	2000	2005	2010	2015	95% confidence interval, 2015
1	Beijing	Beijing	578.2	973.2	1468.8	1691.6	[1684.4, 1698.8]
2	Tianjin	Tianjin	313.4	442.4	593.5	805.9	[802.44, 809.44]
3	Shanghai	Shanghai	670.9	1232.2	1764.1	2272.6	[2262.9, 2282.3]
4	Chongqing	Chongqing	309.4	698.1	1106.9	1461.2	[1456, 1466.4]
5	Inner Mongolia	Hohhot	50.8	99.0	174.2	222.7	[221.79, 223.7]
6	Liaoning	Shenyang	259.3	364.0	546.8	771.7	[768.45, 775.03]
7	Liaoning	Dalian	209.6	243.3	322.6	412.5	[410.73, 414.24]
8	Hebei	Shijiazhuang	199.7	223.0	310.8	500.6	[498.76, 502.38]
9	Shanxi	Taiyuan	285.5	280.4	293.8	338.3	[336.94, 339.68]
10	Heilongjiang	Harbin	234.2	334.7	444.4	634.7	[632.25, 637.2]
11	Zhejiang	Hangzhou	202.9	305.2	426.8	800.6	[797.21, 804.07]
12	Zhejiang	Ningbo	116.6	196.6	314.8	634.7	[631.97, 637.36]
13	Anhui	Hefei	94.6	147.0	260.4	446.8	[444.96, 448.65]
14	Jiangxi	Nanchang	153.1	202.4	264.2	378.9	[377.32, 380.51]
15	Henan	Zhengzhou	237.5	265.3	374.0	507.8	[505.73, 509.9]
16	Hunan	Changsha	168.9	188.5	269.6	379.8	[378.12, 381.56]

17	Guangdong	Guangzhou	149.5	345.9	514.4	839.7	[836.16, 843.31]
18	Guangdong	Shenzhen	234.9	384.9	469.3	520.4	[518.18, 522.64]
19	Sichuan	Chengdu	363.2	473.1	706.2	1029.8	[1025.5, 1034.1]
20	Shaanxi	Xian	242.2	333.9	447.5	641.4	[638.78, 643.97]
21	Fujian	Fuzhou	173.2	237.1	268.6	453.9	[452.03, 455.85]
22	Fujian	Xiamen	120.4	165.2	263.4	421.0	[419.24, 422.77]
23	Jilin	Changchun	200.0	255.8	372.5	515.8	[513.59, 517.95]
24	Hubei	Wuhan	293.2	444.2	579.5	819.1	[815.55, 822.6]
25	Shandong	Jinan	159.6	202.2	247.1	412.9	[411.17, 414.62]
26	Shandong	Qingdao	217.3	380.3	540.5	748.0	[744.73, 751.21]
27	Guangxi	Nanning	116.9	184.5	257.1	325.1	[323.93, 326.2]
28	Hainan	Haikou	48.0	67.6	81.5	97.9	[97.507, 98.229]
29	Guizhou	Guiyang	130.6	176.4	242.8	357.8	[356.38, 359.27]
30	Yunnan	Kunming	229.2	298.6	387.7	486.1	[484.19, 487.92]
31	Gansu	Lanzhou	198.5	229.3	262.1	269.6	[268.52, 270.58]
32	Qinghai	Xining	69.4	87.0	110.7	169.4	[168.77, 169.97]
33	Ningxia	Yinchuan	54.4	92.1	139.2	202.7	[201.89, 203.53]
34	Xinjiang	Urumqi	153.3	230.5	303.2	406.1	[404.43, 407.79]
35	Jiangsu	Nanjing	225.3	279.9	427.2	790.0	[786.65, 793.29]
36	Inner Mongolia	Baotou	76.5	133.9	147.5	192.2	[191.3, 193.01]
37	Inner Mongolia	Hulunbuir	43.5	91.9	132.7	162.2	[161.5, 162.85]
38	Inner Mongolia	Tongliao	19.8	48.3	73.5	115.2	[114.7, 115.66]
39	Inner Mongolia	Chifeng	28.4	77.3	139.4	160.8	[160.26, 161.33]
40	Inner Mongolia	Ulanqab	18.0	44.3	63.8	67.3	[67.011, 67.515]
41	Inner Mongolia	Ordos	9.3	53.3	95.8	118.9	[118.4, 119.42]
42	Inner Mongolia	Bayannur	13.6	43.0	54.9	68.5	[68.215, 68.72]
43	Inner Mongolia	Wuhai	19.3	30.4	38.0	51.9	[51.634, 52.104]
44	Liaoning	Anshan	107.8	126.7	138.7	178.5	[177.74, 179.17]
45	Liaoning	Fushun	80.2	108.1	127.0	162.2	[161.54, 162.8]
46	Liaoning	Benxi	91.7	67.2	84.1	137.1	[136.52, 137.67]
47	Liaoning	Dandong	53.1	61.8	82.8	104.2	[103.87, 104.55]
48	Liaoning	Jinzhou	63.6	83.4	107.0	141.1	[140.63, 141.63]
49	Liaoning	Yingkou	62.0	70.9	117.6	178.5	[177.78, 179.21]
50	Liaoning	Fuxin	35.8	49.6	56.8	92.9	[92.62, 93.228]
51	Liaoning	Liaoyang	40.2	48.2	55.1	65.7	[65.402, 65.905]
52	Liaoning	Panjin	35.2	59.8	67.0	112.7	[112.2, 113.16]
53	Liaoning	Tieling	44.5	58.6	84.5	163.2	[162.63, 163.8]
54	Liaoning	Chaoyang	42.5	60.8	79.3	123.4	[122.99, 123.8]
55	Liaoning	Huludao	45.6	64.3	46.5	61.1	[60.847, 61.254]
56	Hebei	Chengde	33.5	56.9	92.1	139.6	[139.16, 140.07]
57	Hebei	Zhangjiakou	67.8	81.0	138.4	206.4	[205.66, 207.03]

58	Hebei	Qinhuangdao	72.0	93.9	135.1	193.6	[192.95, 194.2]
59	Hebei	Tangshan	149.7	188.1	248.2	362.3	[360.82, 363.82]
60	Hebei	Langfang	43.6	88.8	178.0	313.9	[312.68, 315.07]
61	Hebei	Baoding	101.2	132.2	160.8	282.1	[281.11, 282.99]
62	Hebei	Cangzhou	81.8	95.5	118.2	194.5	[193.79, 195.13]
63	Hebei	Hengshui	33.9	49.8	70.7	117.9	[117.51, 118.3]
64	Hebei	Xingtai	51.2	59.5	74.3	120.7	[120.3, 121.13]
65	Hebei	Handan	114.6	130.5	167.0	256.1	[255.21, 257]
66	Shanxi	Datong	143.5	138.5	141.0	242.1	[241.26, 242.86]
67	Shanxi	Yangquan	59.2	55.8	56.8	73.0	[72.723, 73.23]
68	Shanxi	Changzhi	65.7	71.0	89.3	135.3	[134.88, 135.8]
69	Shanxi	Jincheng	100.1	98.6	104.2	117.4	[117.02, 117.8]
70	Shanxi	Shuozhou	16.9	24.2	37.6	64.5	[64.307, 64.776]
71	Shanxi	Jinzhong	52.8	58.4	76.7	97.7	[97.358, 98.002]
72	Shanxi	Yuncheng	33.8	47.6	86.3	157.1	[156.52, 157.59]
73	Shanxi	Xinzhou	30.6	31.7	40.7	63.7	[63.454, 63.89]
74	Shanxi	Linfen	53.6	58.6	71.4	98.5	[98.096, 98.806]
75	Shanxi	Luliang	28.4	37.6	58.4	71.9	[71.594, 72.254]
76	Heilongjiang	Qiqihar	83.2	110.0	148.3	220.9	[219.99, 221.73]
77	Heilongjiang	Jixi	47.2	45.7	52.9	63.0	[62.745, 63.186]
78	Heilongjiang	Hegang	33.0	36.8	41.3	42.9	[42.762, 43.062]
79	Heilongjiang	Shuangyashan	25.5	28.1	32.9	43.6	[43.429, 43.725]
80	Heilongjiang	Daqing	110.5	120.6	170.0	229.4	[228.37, 230.34]
81	Heilongjiang	Yichun	61.2	61.8	61.2	64.4	[64.169, 64.666]
82	Heilongjiang	Jiamusi	43.9	54.2	84.6	129.0	[128.57, 129.41]
83	Heilongjiang	Qitaihe	19.2	25.1	32.9	37.1	[37.001, 37.27]
84	Heilongjiang	Mudanjiang	92.9	98.6	117.3	146.8	[146.27, 147.3]
85	Heilongjiang	Heihe	22.6	21.7	29.4	50.0	[49.802, 50.137]
86	Heilongjiang	Suihua	51.9	52.0	98.6	166.9	[166.34, 167.5]
87	Zhejiang	Jiaxing	61.9	110.7	188.9	342.1	[340.65, 343.49]
88	Zhejiang	Huzhou	37.0	64.9	100.7	166.1	[165.45, 166.84]
89	Zhejiang	Shaoxing	60.8	106.3	162.7	316.3	[314.99, 317.65]
90	Zhejiang	Zhoushan	32.3	40.9	52.5	96.8	[96.347, 97.19]
91	Zhejiang	Wenzhou	95.0	147.5	209.9	313.8	[312.57, 315.09]
92	Zhejiang	Jinhua	83.2	115.2	153.4	210.6	[209.81, 211.47]
93	Zhejiang	Quzhou	25.6	48.3	73.4	102.5	[102.05, 102.89]
94	Zhejiang	Taizhou	163.9	180.6	194.9	258.4	[257.35, 259.38]
95	Zhejiang	Lishui	26.5	36.8	50.3	74.7	[74.411, 74.951]
96	Anhui	Huaibei	46.4	50.8	60.1	74.7	[74.431, 74.93]
97	Anhui	Suzhou	14.9	20.4	40.1	81.1	[80.845, 81.401]
98	Anhui	Bengbu	50.5	63.3	89.3	151.3	[150.75, 151.79]

99	Anhui	Fuyang	56.5	60.5	78.6	105.3	[104.86, 105.64]
100	Anhui	Huainan	60.6	67.1	92.1	119.4	[119.03, 119.83]
101	Anhui	Chuzhou	34.9	42.2	67.4	151.8	[151.19, 152.31]
102	Anhui	Liuan	18.3	31.6	51.5	89.6	[89.293, 89.934]
103	Anhui	Maanshan	46.3	58.2	93.5	164.7	[164.04, 165.35]
104	Anhui	Wuhu	47.1	61.6	92.6	206.5	[205.68, 207.36]
105	Anhui	Xuancheng	20.6	29.9	52.0	88.5	[88.19, 88.791]
106	Anhui	Tongling	26.3	33.7	46.1	80.3	[79.999, 80.609]
107	Anhui	Chizhou	13.7	19.5	38.4	63.6	[63.381, 63.804]
108	Anhui	Anqing	55.0	69.5	100.0	141.9	[141.46, 142.38]
109	Anhui	Huangshan	17.0	28.2	45.0	64.6	[64.418, 64.841]
110	Jiangxi	Jingdezhen	58.6	72.8	82.1	99.0	[98.609, 99.309]
111	Jiangxi	Pingxiang	53.1	60.5	66.5	71.6	[71.359, 71.874]
112	Jiangxi	Jiujiang	62.4	82.6	112.9	145.6	[144.48, 146.69]
113	Jiangxi	Xinyu	28.5	38.3	57.0	90.5	[90.044, 90.865]
114	Jiangxi	Yintan	25.2	29.7	35.8	50.4	[50.203, 50.585]
115	Jiangxi	Ganzhou	70.4	105.0	172.7	262.5	[261.48, 263.43]
116	Jiangxi	Jian	29.0	50.5	79.3	118.1	[117.73, 118.54]
117	Jiangxi	Yichun	57.4	80.2	106.1	185.3	[184.73, 185.95]
118	Jiangxi	Fuzhou	22.6	47.1	64.0	99.8	[99.39, 100.11]
119	Jiangxi	Shangrao	27.3	56.4	91.1	142.4	[141.89, 142.84]
120	Henan	Kaifeng	55.8	64.9	95.7	164.9	[164.31, 165.41]
121	Henan	Luoyang	116.5	150.4	236.6	336.6	[335.41, 337.83]
122	Henan	Pingdingshan	65.8	75.6	126.1	186.6	[185.93, 187.18]
123	Henan	Anyang	63.2	75.6	123.8	170.1	[169.56, 170.68]
124	Henan	Hebi	26.3	29.6	40.7	59.5	[59.322, 59.734]
125	Henan	Xinxiang	72.8	86.0	156.5	190.3	[189.71, 190.94]
126	Henan	Jiaozuo	62.8	77.9	123.7	144.5	[143.93, 145.02]
127	Henan	Puyang	28.2	50.9	65.2	93.6	[93.324, 93.953]
128	Henan	Xuchang	45.5	63.3	133.7	171.0	[170.39, 171.61]
129	Henan	Luohe	28.2	33.1	44.8	57.7	[57.465, 57.847]
130	Henan	Sanmenxia	31.8	38.1	55.9	74.6	[74.269, 74.833]
131	Henan	Nanyang	71.5	86.6	114.2	155.7	[155.15, 156.32]
132	Henan	Shangqiu	38.7	56.9	98.9	154.1	[153.6, 154.67]
133	Henan	Xinyang	26.9	67.6	185.2	396.7	[395.33, 398.08]
134	Henan	Zhoukou	27.1	42.8	113.1	204.8	[204.02, 205.48]
135	Henan	Zhumadian	14.5	32.1	96.9	207.1	[206.39, 207.75]
136	Hunan	Zhuzhou	82.9	82.9	100.8	130.5	[129.94, 130.96]
137	Hunan	Xiangtan	63.0	64.6	79.9	92.3	[91.888, 92.617]
138	Hunan	Hengyang	93.2	94.2	109.2	143.3	[142.8, 143.74]
139	Hunan	Shaoyang	43.2	46.0	61.0	93.5	[93.145, 93.814]

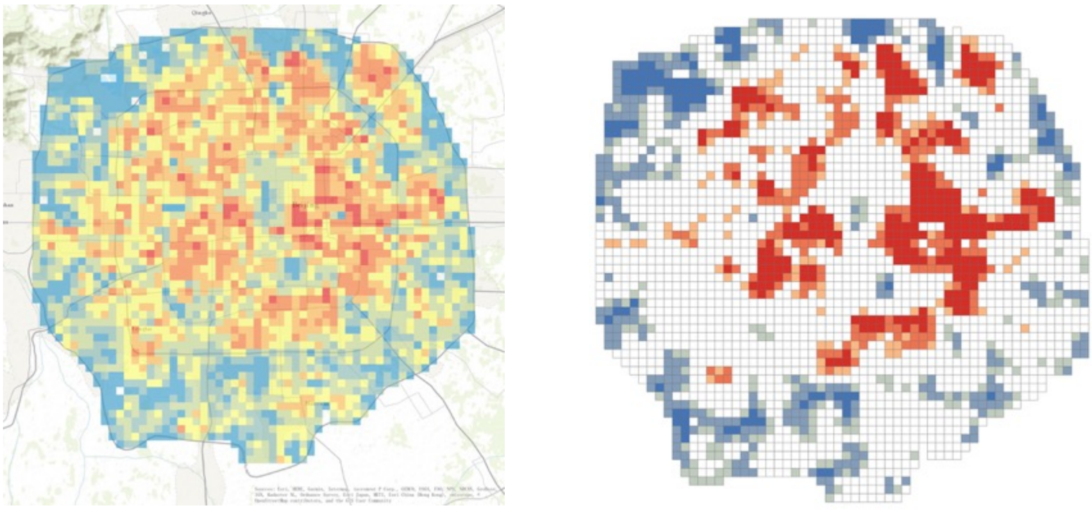
140	Hunan	Yueyang	80.6	82.4	92.0	103.8	[103.45, 104.21]
141	Hunan	Changde	53.4	58.5	81.2	112.8	[112.36, 113.16]
142	Hunan	Zhangjiajie	14.5	15.4	20.2	24.7	[24.614, 24.778]
143	Hunan	Yiyang	27.0	29.2	46.6	66.1	[65.928, 66.358]
144	Hunan	Chenzhou	34.4	43.8	61.3	93.6	[93.236, 93.875]
145	Hunan	Yongzhou	30.9	34.4	52.1	96.9	[96.53, 97.354]
146	Hunan	Huaihua	25.4	29.2	38.5	66.0	[65.739, 66.207]
147	Hunan	Loudi	46.5	47.6	61.4	99.5	[99.117, 99.799]
148	Guangdong	Zhuhai	73.3	95.7	137.5	180.3	[179.5, 181.03]
149	Guangdong	Shantou	144.1	157.6	169.9	199.2	[198.5, 199.88]
150	Guangdong	Foshan	296.6	345.2	375.7	449.5	[447.59, 451.4]
151	Guangdong	Shaoguan	71.8	82.5	102.3	120.7	[120.34, 121.13]
152	Guangdong	Heyuan	22.8	26.6	36.1	52.8	[52.646, 53.008]
153	Guangdong	Meizhou	39.3	48.7	56.4	89.1	[88.73, 89.447]
154	Guangdong	Huizhou	84.5	94.5	152.6	245.0	[243.97, 245.96]
155	Guangdong	Shanwei	30.8	29.0	32.8	34.9	[34.725, 34.977]
156	Guangdong	Dongguan	104.4	120.8	142.2	185.8	[184.99, 186.54]
157	Guangdong	ZhongShan	134.5	162.1	217.9	303.3	[301.98, 304.53]
158	Guangdong	Jiangmen	152.4	171.5	191.2	228.3	[227.45, 229.19]
159	Guangdong	Yangjiang	37.2	43.4	46.6	57.9	[57.696, 58.116]
160	Guangdong	Zhanjiang	96.6	96.4	102.6	127.5	[126.75, 128.31]
161	Guangdong	Maoming	91.5	88.7	94.5	107.8	[107.44, 108.17]
162	Guangdong	Zhaoqing	66.1	80.0	102.3	136.3	[135.85, 136.83]
163	Guangdong	Qingyuan	32.6	44.9	72.3	113.4	[113.01, 113.75]
164	Guangdong	Chaozhou	19.8	24.6	29.1	37.3	[37.132, 37.37]
165	Guangdong	Jieyang	33.1	38.3	47.5	56.2	[56.067, 56.432]
166	Guangdong	Yunfu	52.0	49.8	51.5	62.5	[62.26, 62.737]
167	Sichuan	Zigong	49.8	60.1	74.6	106.7	[106.38, 107.08]
168	Sichuan	Panzhihua	50.7	53.2	61.9	76.1	[75.754, 76.392]
169	Sichuan	Luzhou	53.3	76.5	110.9	162.1	[161.55, 162.61]
170	Sichuan	Deyang	92.7	103.9	121.3	153.3	[152.74, 153.78]
171	Sichuan	Mianyang	78.8	97.6	120.9	183.0	[182.29, 183.62]
172	Sichuan	Guangyuan	28.7	33.7	41.8	63.2	[62.966, 63.386]
173	Sichuan	Suining	33.1	45.6	68.9	99.9	[99.553, 100.23]
174	Sichuan	Neijiang	75.6	83.3	102.9	135.0	[134.51, 135.45]
175	Sichuan	Leshan	65.5	73.4	91.2	110.9	[110.57, 111.31]
176	Sichuan	Nanchong	46.7	70.5	113.9	180.0	[179.42, 180.63]
177	Sichuan	Yibin	27.9	47.3	79.2	149.0	[148.46, 149.49]
178	Sichuan	Guangan	28.1	44.8	72.4	98.0	[97.723, 98.372]
179	Sichuan	Dazhou	29.0	44.0	76.0	119.5	[119.06, 119.92]
180	Sichuan	Yaan	15.7	16.9	20.9	23.2	[23.153, 23.304]

181	Sichuan	Bazhong	13.0	19.3	29.0	45.6	[45.406, 45.721]
182	Shaanxi	Tongchuan	23.1	28.8	31.1	30.9	[30.75, 30.953]
183	Shaanxi	Baoji	45.7	54.7	63.4	63.8	[63.593, 64.049]
184	Shaanxi	Xianyang	48.6	58.6	66.6	69.3	[69.08, 69.549]
185	Shaanxi	Weinan	38.5	49.5	70.1	102.4	[102.09, 102.78]
186	Shaanxi	Hanzhong	17.3	35.4	51.1	79.9	[79.626, 80.164]
187	Shaanxi	Ankang	19.3	33.0	41.8	54.2	[54.019, 54.383]
188	Shaanxi	Shangluo	6.7	8.2	10.3	13.9	[13.808, 13.908]
189	Shaanxi	Yanan	6.7	12.1	16.7	19.5	[19.385, 19.531]
190	Shaanxi	yulin	10.0	19.7	36.3	63.4	[63.146, 63.669]
191	Fujian	Putian	12.6	20.4	34.4	99.5	[99.143, 99.923]
192	Fujian	Sanming	48.4	55.0	68.8	116.0	[115.56, 116.5]
193	Jilin	Siping	42.4	48.6	65.4	78.8	[78.536, 79.054]
194	Hubei	Huangshi	56.7	63.1	74.9	95.0	[94.629, 95.323]
195	Hubei	Shiyan	56.7	64.0	85.3	126.5	[126.09, 126.94]
196	Hubei	Jingzhou	188.9	183.7	183.3	197.6	[196.9, 198.23]
197	Hubei	Yichang	103.8	115.6	130.7	194.7	[193.85, 195.45]
198	Hubei	Huanggang	58.8	64.7	82.4	138.9	[138.43, 139.35]
199	Shandong	Zibo	114.0	153.1	188.1	242.9	[241.86, 243.89]
200	Shandong	Dongying	69.4	102.3	143.1	193.9	[193.09, 194.74]
201	Shandong	Yantai	140.1	200.6	276.2	386.1	[384.47, 387.7]
202	Shandong	Jining	75.7	118.6	206.8	299.2	[298.12, 300.22]
203	Shandong	Weihai	70.6	97.9	158.6	283.4	[282.17, 284.59]
204	Shandong	Liaocheng	29.3	53.2	71.5	125.1	[124.68, 125.52]
205	Shandong	Linyi	60.1	80.6	115.1	221.8	[220.99, 222.51]
206	Shandong	Heze	15.7	26.9	67.0	139.9	[139.42, 140.46]
207	Jiangsu	Wuxi	154.7	207.5	338.3	657.7	[654.84, 660.49]
208	Jiangsu	Xuzhou	99.7	123.1	159.8	280.6	[279.45, 281.67]
209	Jiangsu	Changzhou	101.8	145.5	258.8	542.0	[539.67, 544.33]
210	Jiangsu	Suzhou	196.2	332.6	643.4	1118.1	[1113.2, 1123]
211	Jiangsu	Nantong	85.5	117.1	192.2	428.7	[426.93, 430.48]
212	Jiangsu	Lianyungang	42.0	61.9	109.1	183.3	[182.68, 183.98]
213	Jiangsu	Yancheng	44.5	64.1	117.6	256.9	[255.87, 257.85]
214	Jiangsu	Yangzhou	81.9	112.9	167.1	310.6	[309.23, 311.9]
215	Jiangsu	Zhenjiang	73.4	89.3	119.9	236.8	[235.8, 237.81]

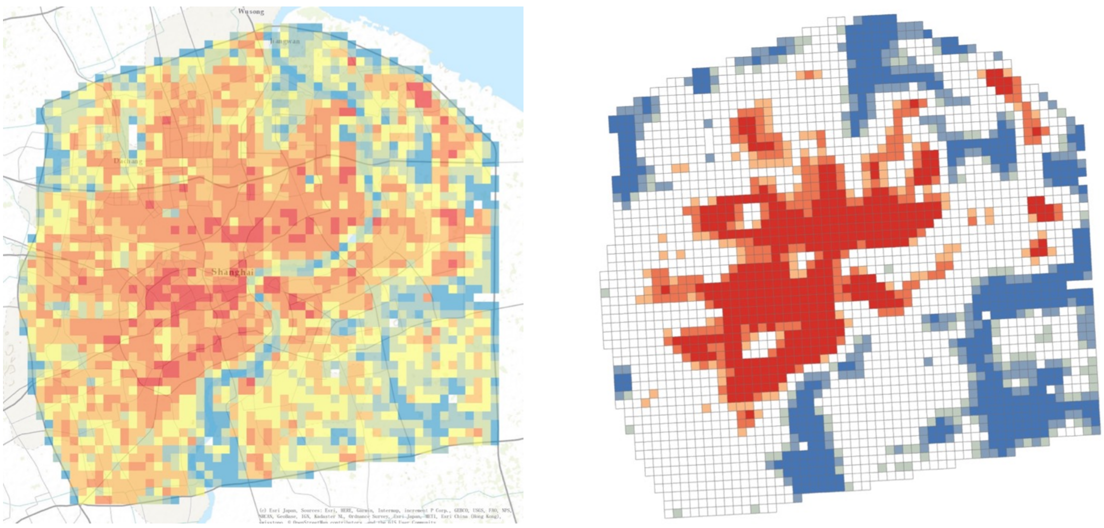
Appendix 3. Building MS spatial distribution and hot spot analysis results of 14 metropoles

*The following figures share the same legend at the end of this file. The pixel unit in each figure is 500m*500m (0.25 km²).*

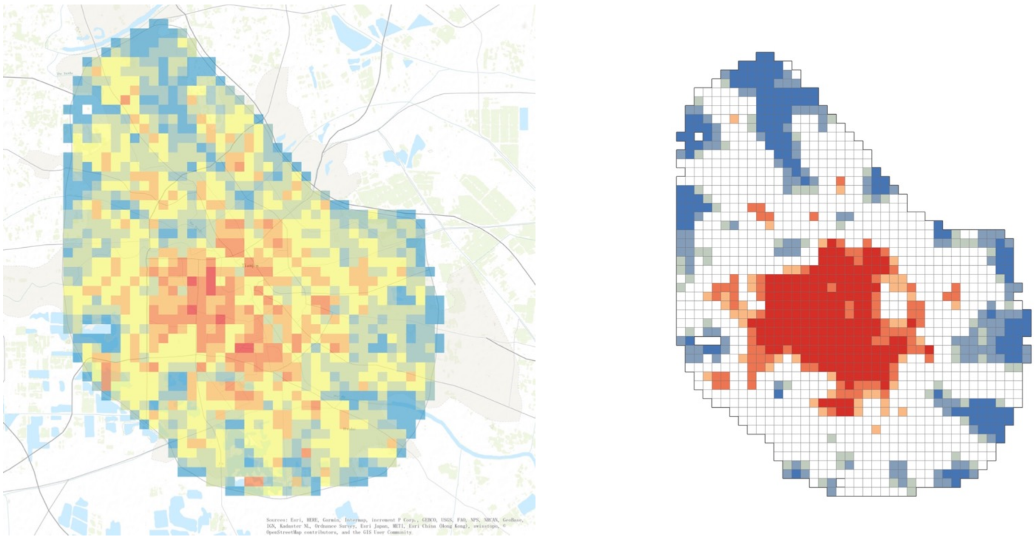
Building MS spatial distribution (Mt/km²) | Hot spot analysis result



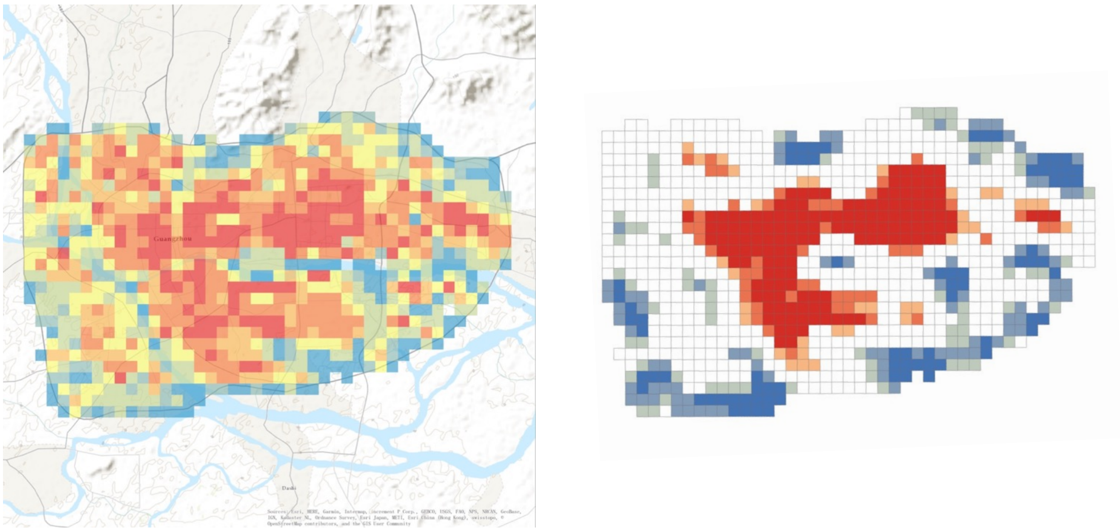
(1). Beijing



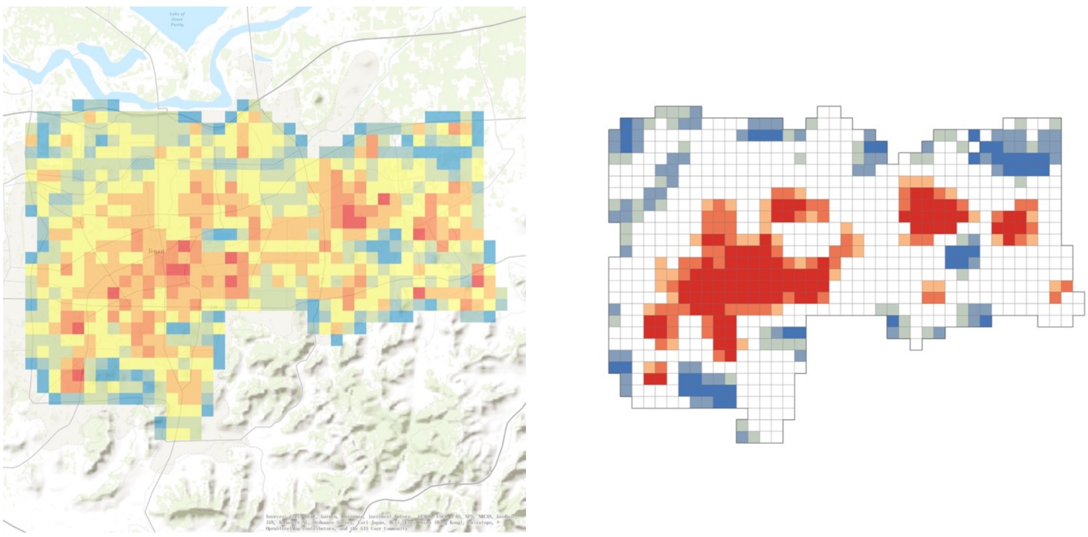
(2). Shanghai



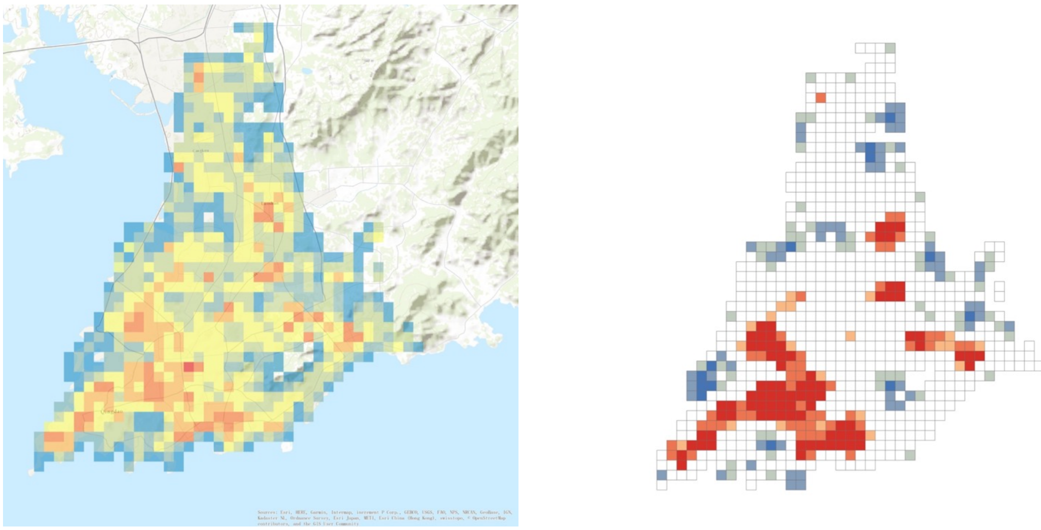
(3). Tianjin



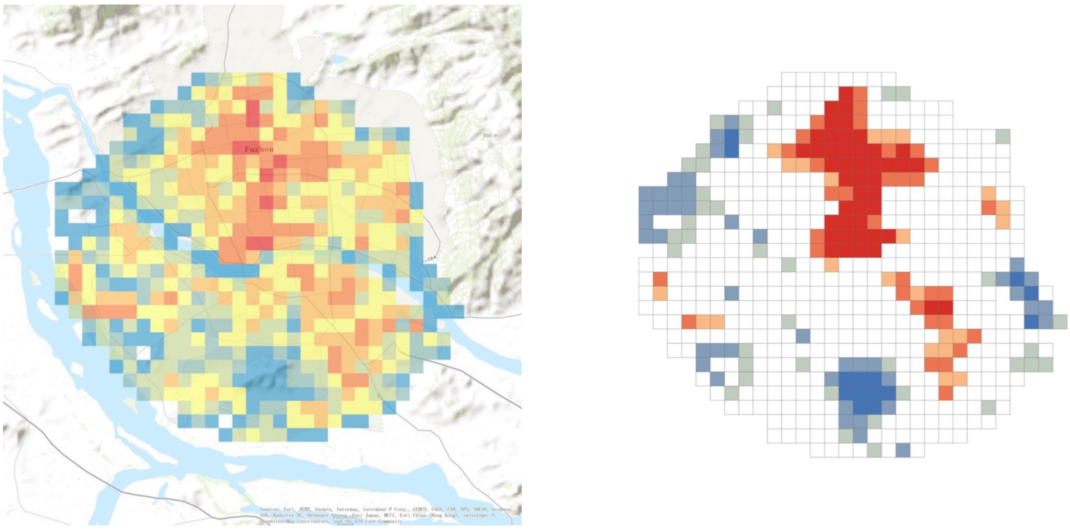
(4). Guangzhou



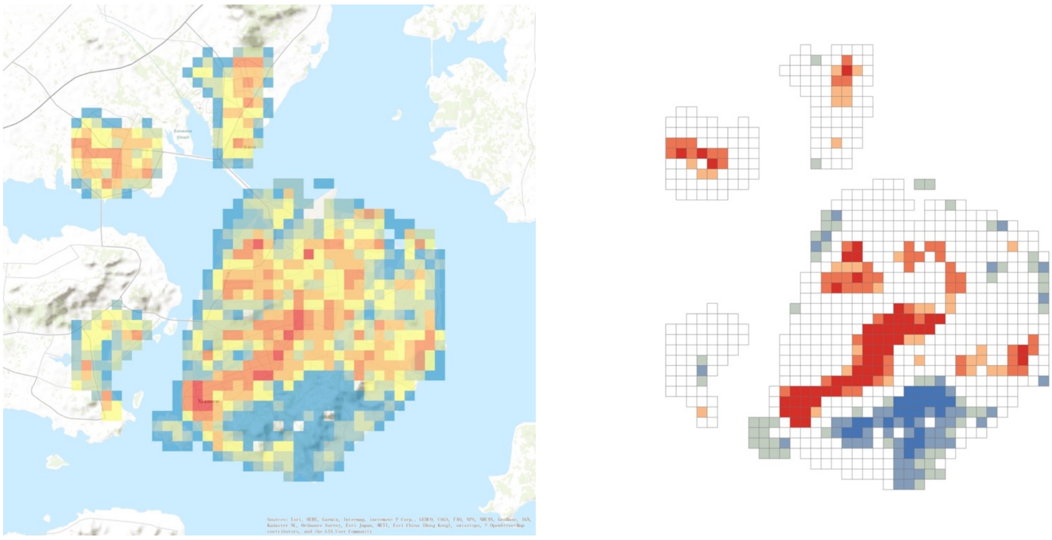
(5). Jinan



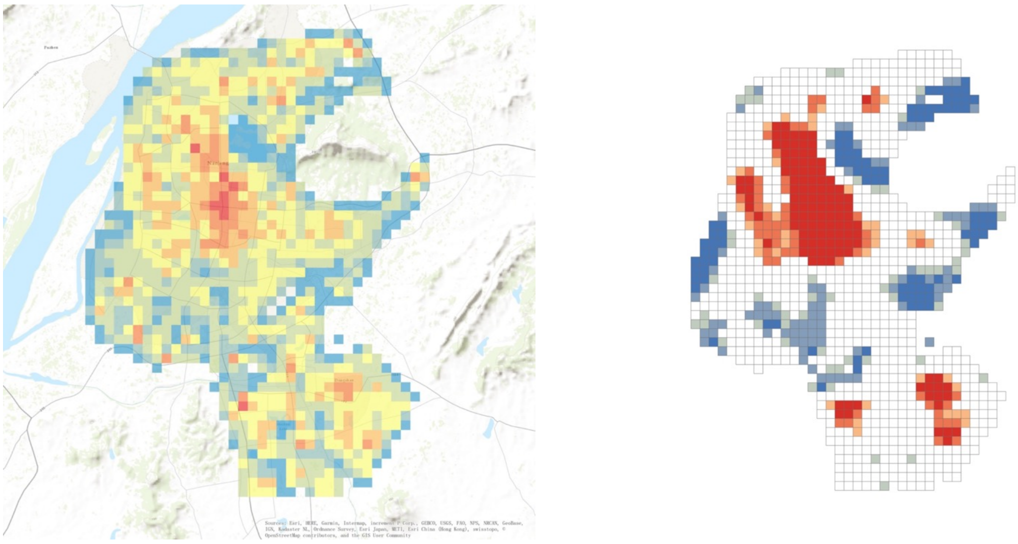
(6). Qingdao



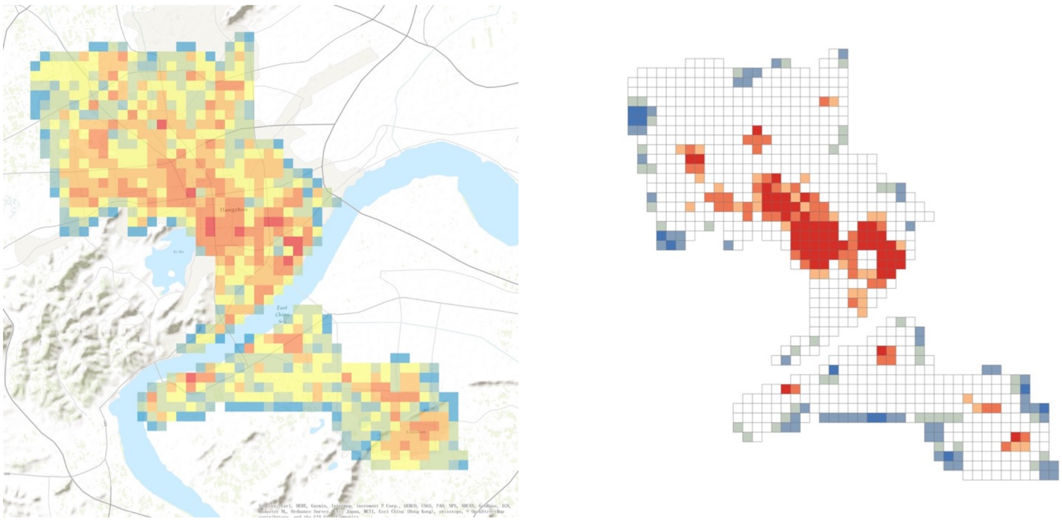
(7). Fuzhou



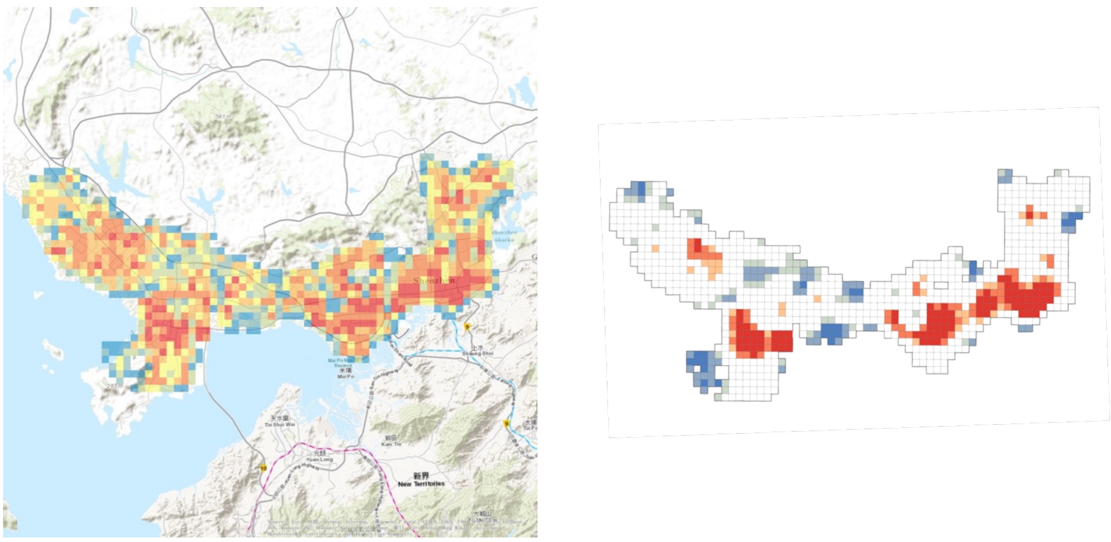
(8). Xiamen



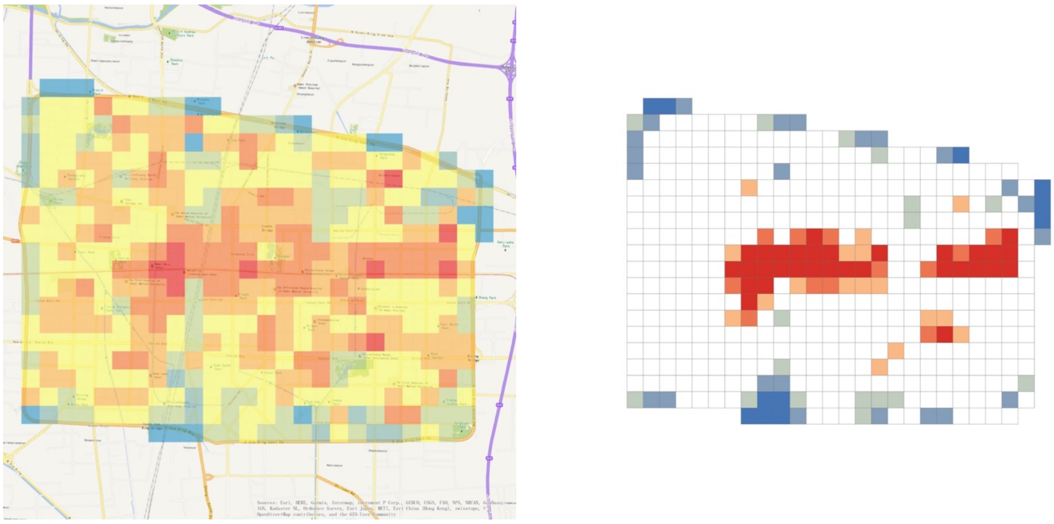
(9). Nanjing



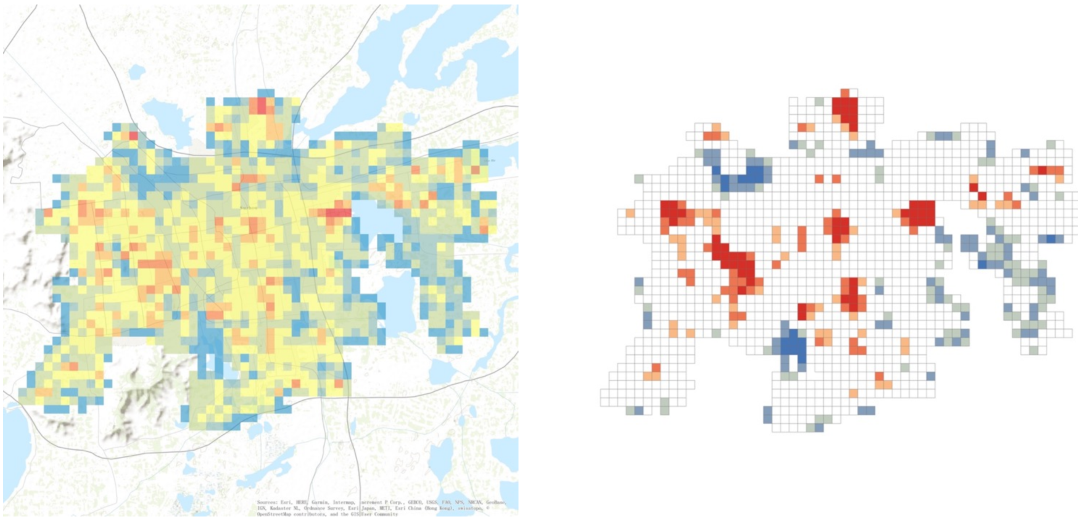
(10). Hangzhou



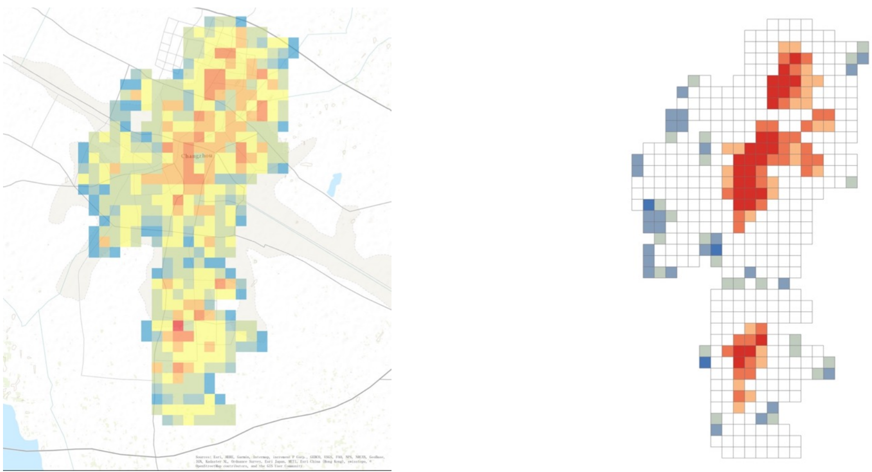
(11). Shenzhen



(12). Shijiazhuang



(13). Suzhou



(14). Changzhou

Appendix 4. Sources and uncertainty levels for 4d-GIS database

Attribute	Year	Sources	UL
Geographical location and shape	2018	Baidu Maps (Digitalized map with height)	1
	2011, 2008, 2004, 2002	Google Earth (Satellite image)	1
	1997	Aerial image	1.5
	1986	Paper map	2
	1978	Shenyang topographic map 1978 (Shenyang Municipal Archives)	2
	1968	Shenyang topographic map 1968 (Shenyang Municipal Archives)	2.5
	1947	Shenyang topographic map 1947 (Shenyang Municipal Archives)	2.5
	1932	Map of Mukden, Manchukuo 1932 (Shenyang Municipal Archives)	3
	1910	Mukden Map 1911 (Shenyang Municipal Archives)	3
Typology	2018, 2011, 2008	Gaode Maps (Points of Interest Data)	1
	2002, 2004	Google Earth (Satellite image)	1.5
	1997	Aerial image	1.5
	1910-1986	Same maps as above	2
Floor number/ Height	2018	Baidu Maps (see above)	1
	2011, 2008, 2004, 2002	Google Earth (Satellite image, estimated based on the shadow and the known height of buildings)	2
	1910-1997	Documentary material (Editorial Committee of Local chronicles, 1998; Liu, 2016; Politicl Consultative Conference, 2008, 2017; *Shenyang Ten Years*, 1959) Old photos in books (CPPCC Shenyang Tiexi District Committee Literature and History Committee, 2006; *Shenyang*, 1955)	3.5

Appendix 5. Fitted survival curves

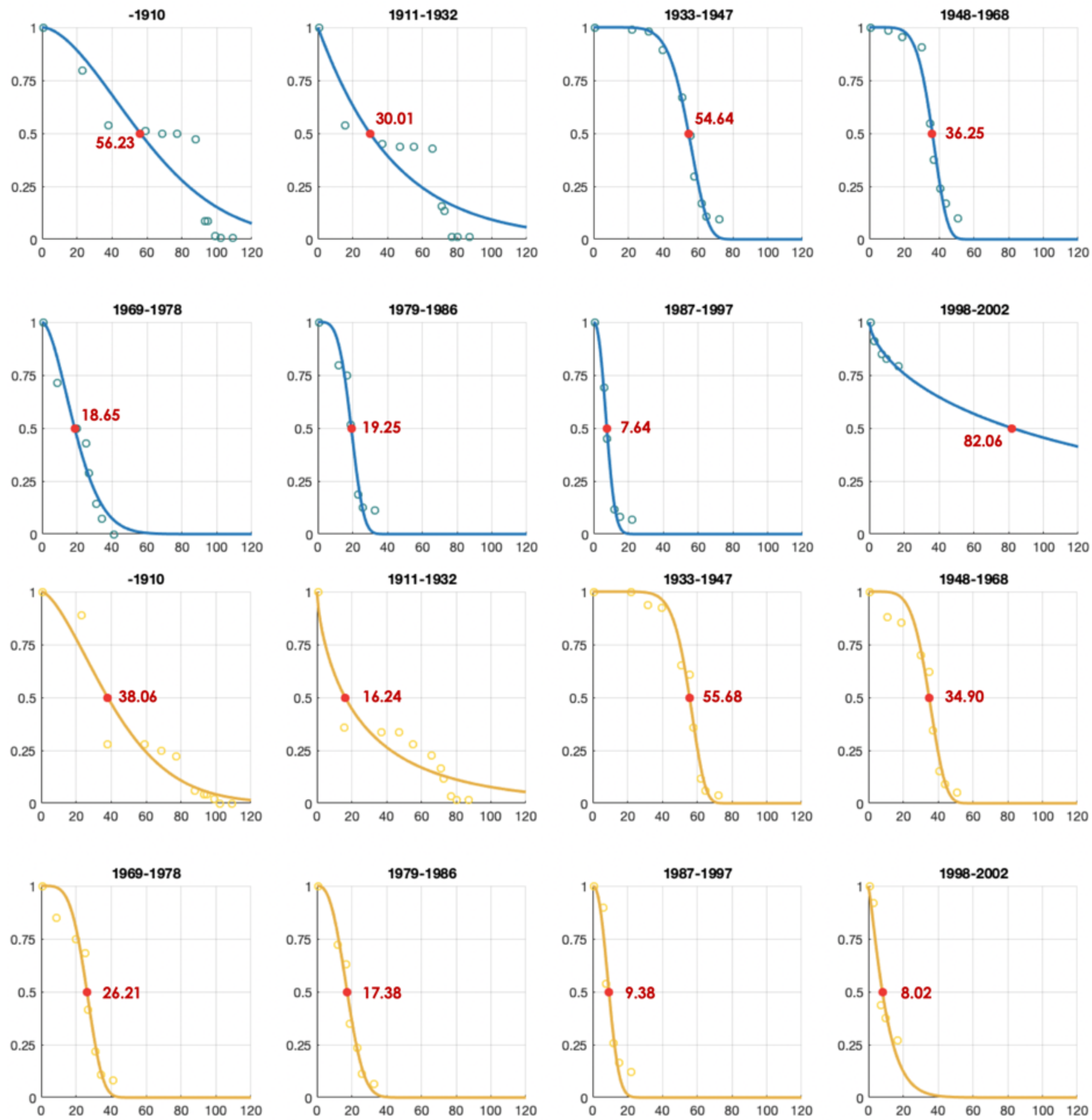


Figure S1. Fitted survival curves modeled with the Weibull distribution for residential buildings (blue) and industrial buildings (yellow)

Table S1. Fitted parameters for the Weibull survival curves

Cohort	Residential			Industrial		
	λ	k	R^2	λ	k	R^2
-1910	69.42	1.74	0.82	48.05	1.57	0.93
1911-1932	42.91	1.02	0.82	27.00	0.72	0.89
1933-1947	57.63	6.88	0.99	58.10	8.59	0.98
1948-1968	38.56	5.96	0.97	37.44	5.21	0.95
1969-1978	23.05	1.73	0.95	28.62	4.17	0.95
1979-1986	21.16	3.87	0.96	19.98	2.63	0.97
1987-1997	8.93	2.34	0.99	10.93	2.39	0.95
1998-2002	144.84	0.65	0.91	10.86	1.21	0.92

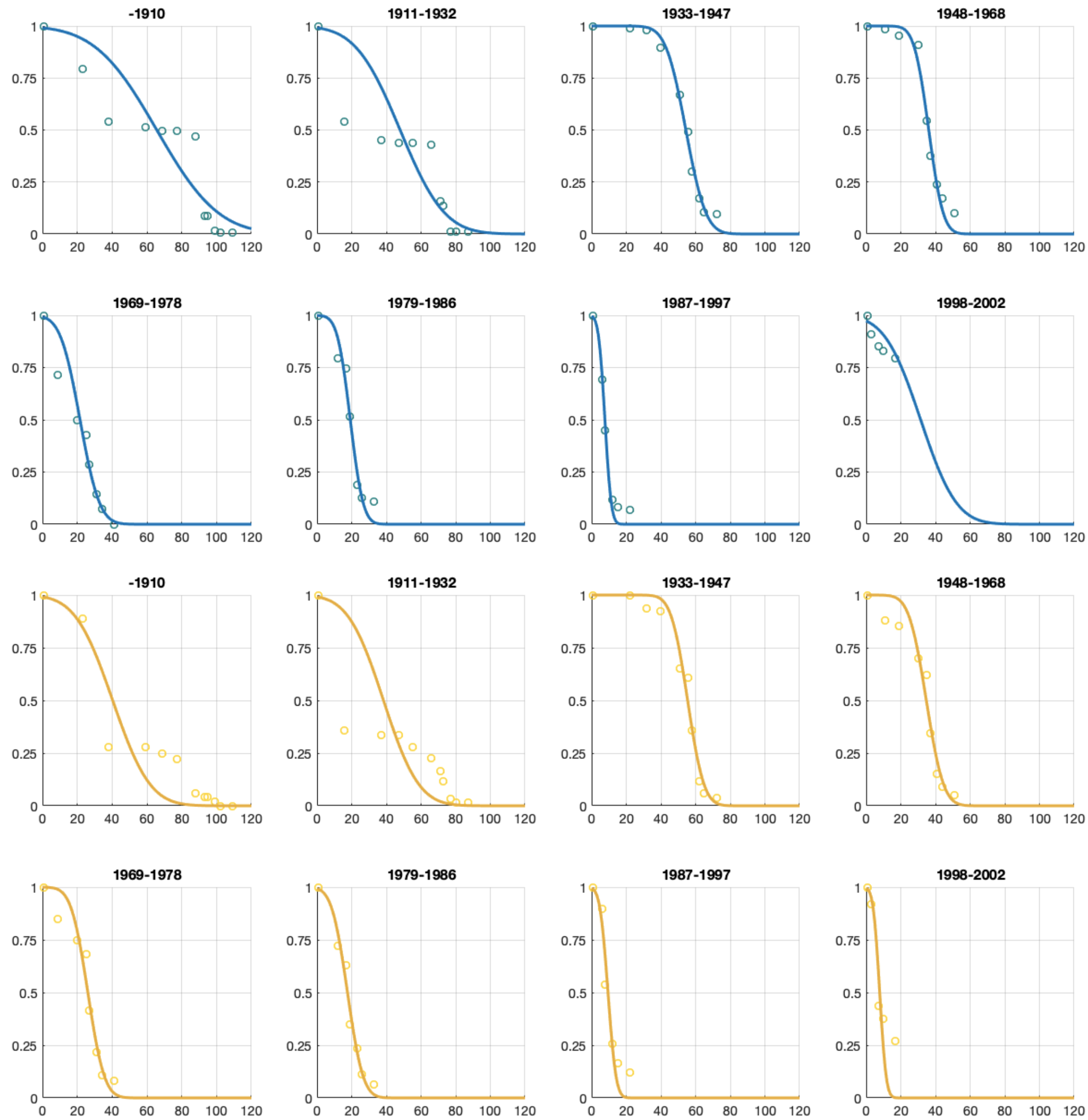


Figure S2. Fitted survival curves modeled with the Normal distribution for residential buildings (blue) and industrial buildings (yellow)

Table S2. Fitted parameters for the Normal distribution survival curves

Cohort	Residential			Industrial		
	μ	σ	R^2	μ	σ	R^2
-1910	65.66	27.79	0.80	40.34	16.91	0.85
1911-1932	47.95	20.18	0.66	38.36	16.06	0.43
1933-1947	54.41	9.11	0.99	55.42	7.45	0.97
1948-1968	36.13	6.57	0.98	34.73	7.84	0.95
1969-1978	21.58	8.85	0.93	26.08	7.51	0.95
1979-1986	19.20	5.86	0.96	17.59	7.13	0.97
1987-1997	7.71	2.89	0.98	9.49	3.65	0.94
1998-2002	29.47	17.31	0.67	7.84	2.94	0.72