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Residential building stock modelling for mainland China

Danhua Xin[1], James Edward Daniell[1,2,*], Hing-Ho Tsang[3], Friedemann Wenzel[1]

[1]Center for Disaster Management and Risk Reduction Technology (CEDIM) and Geophysical Institute, Karlsruhe Institute of Technology, Hertzstrasse 16, 76187, Karlsruhe, Germany

[2]General Sir John Monash Scholar, The General Sir John Monash Foundation, Level 5, 30 Collins Street, Melbourne,Victoria, 3000, Australia

[3]Centre for Sustainable Infrastructure, Swinburne University of Technology, Melbourne, VIC 3122, Australia

[*]*Correspondence to* James Edward Daniell (j.e.daniell@gmail.com)

Abstract

Previous seismic damage reports have shown that the damage and collapse of buildings is the leading cause of fatality and property loss, especially in developing countries. To better serve the risk analysis targeted at near-real-time post-earthquake mitigation and pre-earthquake preparedness and resources allocation, this study develops a fully reproducible grid-level residential building stock model for mainland China, by disaggregating urbanity level census data of each province into 1km×1km scale and using population density profile as the proxy. To evaluate the model performance, the modelled residential building stock value is compared with the net capital stock value in Wu et al. (2014) using perpetual inventory method at provincial level. The modelled stock values in these two studies are in good agreement for all the 31 provinces in mainland China. Furthermore, district level comparison of the residential floor area developed in this study with records from statistical yearbook of Shanghai is also conducted. It turns out that the floor area developed in this study is compatible with floor area recorded in the yearbook of Shanghai. To further validate the applicability of the modelled results in seismic risk assessment, an estimation of the scenario loss to modelled residential buildings is performed, by assuming the recurrence of 2008 Wenchuan M8.0 earthquake. The overall estimated loss approximates the loss value derived from damage reports based on field investigation quite well. Both results indicate the reliability of the residential building stock model developed in this study. The limitations of this study are discussed and directions for future work are recommended.

1. Introduction

With the theme of last year's International Day for Disaster Reduction (IDDR2018) being "Target B: Reducing the number of affected people by disasters by 2030", the awareness of the impacts of natural disasters on human society has been increasing over the years. Demands from public sector for quantification of disaster risk is thus more urgent than before. As stated by António Guterres, the current United Nations Secretary-General, in IDDR2018, that "Disasters cost hundreds of billions of dollars (every year), hitting the poorest countries disproportionately and pushing millions into poverty. We must tackle disaster risks and leave a more resilient planet to future generations." To better cope with the frequent occurrence of earthquakes and other natural hazards (typhoon, flood, tsunami, etc.), the development of sound risk models for natural hazards should be given top priority, since these hazards can lead to tremendous and often crippling economic losses especially in the countries of the developing world. According to the estimation in Daniell et al. (2011, 2017), from 1900-2016, 2.3 million earthquake fatalities from 2233 fatal events occurred worldwide, with economic losses (direct and indirect) associated with the occurrence of over 9,900 damaging earthquakes reached USD 3.41 trillion (in 2016 price level).

To develop a seismic risk model, three layers of information are essential: hazard, exposure and vulnerability. Hazard refers to the occurrence frequency and severity of ground shakings generated by earthquakes. Exposure captures the attributes of exposed elements in terms of value, location and relative importance (e.g. buildings, critical facilities and infrastructure) to potential earthquake. Vulnerability describes the susceptibility of those exposed elements to earthquake. Among the exposed elements, buildings are considered as the most important asset category in seismic risk assessment, since the majority of loss and fatality that occurs during earthquakes are related to building damage and collapse (Neumayer and Barthel, 2011; Yuan, 2008). As such, estimation of the building stock and the values at risk is an important and integral part of any risk modeling effort. Specifically in developing and disaster vulnerable countries like China, rapid urbanization process has led to massive increase in both the asset value and population exposed to seismic hazards (Hu et al., 2010; Yang and Kohler, 2008). Therefore, a country-level modelling of the building stock and its spatial distribution across China is essential.

Ideally, if the building stock value of the research portfolio is already known, e.g. in an insurance portfolio, building attributes (i.e. the location, geometry, height, construction age and material, occupancy type etc.) are used mainly for building vulnerability determination. However, in most cases, the building stock value is not available and obtaining such detailed information for every building in a large region is not practicable. Therefore, the aforementioned building attributes, which are usually provided at administrative level in census data, are also used to estimate the building stock value. In this case, appropriate proxy (e.g. population density) is required to disaggregate administrative level census data into finer scale. The use of proxy is quite a reasonable approach in dasymetric modelling and has been frequently adopted in previous studies (e.g. Gunasekera et al., 2015; Silva et al., 2015; Thieken et al., 2008).

When disaggregating census data into a finer scale, it cannot be carried out by simply assuming that the assets within an administrative unit are evenly distributed, since in reality people and buildings tend to be concentrated in settlements e.g. along the riverside or within alluvial plains (Figueiredo and Martina, 2016). In this regard, more sensible techniques have been applied and documented in the literature. For example, Silva et al. (2015) disaggregated the building stock at parish level for mainland Portugal based on the population density profile at 30×30 arc-sec resolution cells from LandScan. The LandScan population density profile was produced by apportioning best available census counts into cells based on probability coefficients, which in turn were derived from road proximity, slope, land cover and night-time lights (Dobson et al., 2000).

In mainland China, the modelling of building stock value and its spatial distribution across China is scarcely done at high-resolution (e.g. 1km×1km scale). In those published studies related to building stock model development, e.g. Yang and Kohler (2008) and Hu et al. (2010), the simulation and evolution of building stock value (taking the mainland China as a whole) were designed and targeted for resource consumption and environmental impacts purposes, which cannot meet the needs in risk analysis due to their coarse resolution. International projects e.g. PAGER (Jaiswal et al., 2010) and Gunasekera et al. (2015) also conducted global exposure modelling that covered the building stock value in mainland China. However, these global models cannot fully make use of the census

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data available in each country and usually assuming a uniform distribution of building stock value per capita for each province or even for each country, which might be convenient, but not realistic, especially for unevenly developed countries like China. A recent work of Wu et al. (2018) established a high-resolution (1km×1km scale) asset value model based on the net capital stock value they estimated for 344 prefectures in mainland China using the perpetual inventory method (Wu et al., 2014). However, their original asset data to be disaggregated into grid level was actually restricted to prefecture level. Furthermore, the extent of the natural hazards, in most cases, are dependent on the geological structure (earthquakes) or along the riverside (floods), instead of being restricted to administrative boundaries. Therefore, to better cope with this spatial mismatch between natural hazards and administrative boundaries, building stock models should be geo-coded with relatively high resolution and be disaggregated from more detailed census data.

The organization of the following sections is as follows: the full list of data sources needed, and a detailed description of the methodology used to develop the high-resolution building stock for mainland China will be firstly introduced. Then, to evaluate the model performance, provincial and district level comparison of the modelled results with that in previous studies and yearbook records will be conducted. Finally, an application of the building stock model in seismic risk analysis will also be given.

2. Data Sources and Methodology

This section will introduce in detail the building related census data needed to develop the building stock model and the methodology used to disaggregate the administrative level census data into grid level. The census data used in this study for building stock modelling are extracted from the Tabulation of the 2010 Population Census of the People's Republic of China (hereafter abbreviated as the "2010-census"), particularly for residential buildings. Like in most countries of the world, the national level population and housing census are carried out at 10-year interval, and currently the latest version was issued in 2010. In the 2010-census, there are two types of tables: Long Table and Short Table. Long Table includes summaries based on the surveys of 10% of the total population in mainland China, while the Short Table summaries are based on the surveys of the whole population. Building stock model related census data (e.g. building occupancy type, height classes, construction material, etc.) are extracted from the Long Table of the 2010-census. Supplementary demographic information (e.g. the total population, the average number of people per family and average floor area per person) are extracted from the Short Table of the 2010-census. The data of the 2010-census are summarized in Table 1.

In the 2010-census, for each of the 31 provinces, autonomous regions and municipalities in mainland China (hereafter, all referred to as provinces), the building related census data in the Long Table are categorized into three urbanity levels (urban, township and rural), based on the administrative belonging of the surveyed population. The building related census data for each urbanity level of each province are listed in Table 2. Compared with provincial level census data used in previous studies, one advantage of the 2010-census data is its further categorization of data into three urbanity levels, which better reflects the regional difference within each province.

To disaggregate the urbanity-level based census data into grid-level, population density is used as the proxy, as is a common practice in risk analysis (Aubrecht et al., 2013). The population density profile chosen in this study is developed by Global Human Settlement (GHS) project of the European Commission in 2015, which was

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disaggregated from census or administrative units to geo-girds, informed by the distribution and density of built-up area as mapped in their Global Human Settlement Layer (it is worth noting that this dataset has been updated in 2019). In the 2015 GHS population density profile, the number of population in each geo-grid is given. When compared to values from population counts they prove to be accurate (Gunasekera et al., 2015). The original resolution of the 2015 GHS population density profile is 250m×250m, for calculation convenience it is resampled to 1km×1km resolution before further analysis. The provincial boundary (level 1) vector layer dataset defining the spatial boundaries of mainland China is from the Global Administrative Areas (GADM, www.gadm.org).

With these data on population and residential building stock, a top-down spatial scaling method will be performed to disaggregate the urbanity-level census data into 1km×1km resolution grids for each province in mainland China. The flowchart in Fig. 1 provides an overview of this modelling process. Detailed explanations of each component and step are as follows.

2.1: Assign urbanity attribute (urban/township/rural) to the geo-coded grids in the 2015 GHS population density profile

As outlined above, the population and housing related census data for each of the 31 provinces in mainland China are categorized into three urbanity levels: urban, township and rural. Therefore, the geo-coded grids in 2015 GHS population density profile should also be assigned with an urbanity attribute first, before disaggregating the urbanity-level based census data into each grid. For each province, this is achieved by applying the population reallocation approach developed by Aubrecht et al. (2015) and also illustrated in detail in Gunasekera et al. (2015).

Following this population reallocation approach, the urban/township/rural population proportion of each province can be derived from the Short Table of the 2010-census (as listed in Table 2). For example, in Shanghai City (which is one of the four municipalities in China), the population proportion of urban/township/rural urbanity level is 76.64%, 12.66% and 10.7%, respectively. Then the grids (1km×1km) in 2015 GHS population density file of Shanghai are sorted from the largest to the smallest, and the population in those largest and most populated geo-codes grids are summed up and selected until the 2010-census urban population share (i.e. **76.64%** for Shanghai) is reached. These selected grids are thus assigned with urbanity attribute "urban". The smallest population of these selected grids is taken as the threshold to divide urban and non-urban grids (for Shanghai this urban/non-urban population density threshold is **4827** per km^2). For the remaining non-urban grids, the same process is repeated iteratively until the township population proportion (i.e. **12.66%** for Shanghai) is reached. These secondly selected grids are assigned with urbanity attribute "township" and the smallest population among these grids is taken as the threshold to divide township and rural grids (for Shanghai this township/rural population threshold is **2736** per km^2). The remaining grids are thus assigned with "rural" attribute. The distribution of the assigned urban/township/rural grids in Baoshan District of Shanghai City is shown in Fig. 1 as an example.

Reiterate the above calculations for all the 31 provinces in mainland China, then all the geo-coded grids in the 2015 GHS population profile can be assigned with urban/township/rural attribute accordingly. The corresponding population thresholds for each province are provided in Appendix Table A1.

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2.2: Step 1-Extract the building related census data from the Long Table of the 2010-census (statistics derived from surveys of 10% population of mainland China.

As in many other countries, the population and housing census data in mainland China are particularly surveyed for residential buildings. Therefore, the building stock model developed in this study is for residential building stock. Related census data for assessment of residential building stock value include the number of families living in building types grouped by building occupancy (i.e. residential, commercial, mixed), by number of storey (i.e. 1, 2-3, 4-6, 7-9, ≥10), and by construction material (i.e. steel/reinforced-concrete, mixed, brick/wood, other; hereafter steel/reinforced-concrete is abbreviated as steel/RC; and “mixed” refer to different combinations of masonry buildings). As already listed in Table 1, these data are extracted from the Long Table of the 2010-census, based on the survey of 10% of the total population in mainland China. Therefore, to evaluate the whole building stock value across China, these building related 2010-census data should be extended from 10% to 100% population first by multiplying the factor of 10 (namely factor *F0* in Step 1-1 of Fig. 1).

After multiplying the factor of 10, the overall number of families living in building types grouped by building storey or construction material is considered to be complete for each urbanity level of each province. With the family number living in each building type known, by multiplying the average number of population per family (namely factor *F1* in Step 1-2 of Fig. 1), which is also provided in the Short Table of the 2010-census, the overall population living in building types grouped by storey (1, 2-3, 4-6, 7-9, ≥10) or construction material (steel/RC, mixed, other, brick/wood) can thus be instantly derived for each province and each urbanity level.

Up to now, the geo-coded grids in the 2015 GHS population density profile have been assigned with urbanity attribute and the population living in each building type is also derived for each province and each urbanity level from the 2010-census. It is noteworthy that the changes in population or building from 2010 to 2015 has not been considered yet. In rapid urbanization countries like China, the bloom of construction of buildings and the population inflow from township/rural areas to urban areas are significant. Therefore, the population derived from the 2010-census needs to be further amplified to the 2015 level, and mathematically this amplification factor (factor *F2* in Step 1-3 of Fig. 1) is assumed to be equal to the ratio between 2015 GHS population and 2010-census derived population (after amplified from 10% to 100% of the population).

As listed in the last column in Table 2, the amplification factor *F2* varies across each urbanity level of each province (namely factor *F2* in Step 1-3 of Fig. 1). For each province, *F2* in the urban area is generally higher than in township/rural area, which is quite reasonable. However, it should be noted that the increase in building construction area from 2010 to 2015 is also assumed to be equal to the population increase. The reason behind such an assumption and the performance of the residential building stock model will be further evaluated in the Results and Discussion section.

After getting the population living in each urbanity of each province amplified to year 2015, now this urbanity-level based population data can be disaggregated into the geo-coded grids in 2015 GHS population density profile by using the apportionment weight (namely factor *F3* in step 1-4 of Fig. 1). *F3* is defined as the population share of each grid relative to the summed population from grids within the same urbanity level of each province.

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2.3: Step 2-Disaggregate population and building related census data from urbanity level into grid level.

As explained in Section 2.2, by multiplying the original building related records extracted from the 2010-census with factor *F0, F1, F2* and *F3* in Step 1 of Fig. 1, the population in each grid living in building types grouped by number of storey (1, 2-3, 4-6, 7-9, ≥10) or by construction material (steel/RC, mixed, other, brick/wood) can be derived.

To estimate the residential building stock value, the number of buildings with combination of both storey class and construction material need to be derived. Initially, from the five storey classes (1, 2-3, 4-6, 7-9, ≥10) and the four building material classes (steel/RC, mixed, other, brick/wood), there will be 20 building sub-types. In the following description, we will first introduce how to reduce the principal number of building sub-types from 20 to 17 based on necessary assumption. Then we will estimate the number of population living in each of the 17 building sub-types. Based the information on average floor area per capita in each urbanity level (as given in the Short Table of the 2010-census), the total floor area of each of the 17 building sub-types in each grid can be derived. Finally, for each building sub-type, their replacement value emerges from a multiplication of the floor area with the construction price.

It is widely observed that most brick/wood buildings are with quite low height (1 or 2-3 storey), while steel/RC buildings are generally quite high with height of 10-storey or above. Therefore, it is further assumed that for "brick/wood" building type, there are only two storey classes (1, 2-3). While for "steel/RC", "mixed", and "other" building types defined in the 2010-census, all five storey classes (1, 2-3, 4-6, 7-9, ≥10) are available (namely *Assumption 1* in Step 2-1 of Fig. 1). Thus, the building sub-types in each grid are reduced from 20 to 17. The list of these 17 building sub-types is given in Table 3.

Currently, we know from Step 1 for instance in each grid the number of population living in buildings of the five storey classes, but do not know for each storey class how the population are distributed in the classes of the four construction materials. Also, we know for instance how many people live in steel/RC buildings but do not know how they are distributed into the five storey classes. The derivation of the number of population in each of the 17 building sub-types requires to find 17 unknowns from 9 equations. In order to solve this underdetermined linear problem, further reasonable approximations need to be made (namely *Assumption 2* in Step 2-2 of Fig. 1) to make sure that in each grid the sum of population living in the 17 building sub-types is equal to the population living in building types grouped by construction material or by storey class.

From here, the population living in each of the 17 building sub-types is derived by a series of distribution steps based on a prioritized ranking of building types and storey class from the aggregated inputs:

1. In each grid, brick/wood buildings are first placed into 1 storey class and subtracted from the total amount of brick/wood buildings.

2. Remaining brick/wood buildings are placed into 2-3 storey class.

3. 10 storey values are placed in steel/RC class as a start as they are assumed to not be "mixed" masonry class.

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4. Similarly, the remaining steel/RC buildings are proportioned to other storey classes from highest to lowest, assuming that the least population in steel/RC would be in 1 storey class.

5. For "other" buildings, they are distributed into each of the five storey classes, based on the proportions of remaining buildings in each storey class (all four construction materials are considered) and the ratio between "other" buildings and "other + mixed" buildings.

6. For "mixed" buildings, they are distributed each of the five storey classes, based on the proportions of remaining buildings in each storey class (all four construction materials are considered) and the ratio between "mixed" buildings and "other + mixed" buildings.

The MATLAB script illustrating the above multi-variate equation solving process is provided in Data/Code Availability section.

2.4: Step 3-Derive the number of people living in each of the 17 building sub-types

With necessary assumption and approximation and by solving the multi-variate equations mentioned in Section 2.3, the population living in each of the 17 building sub-types can be derived for each grid. In the Short Table of 2010-census, the average residential floor area per capita is also given for each urbanity level of each province (namely factor *F4* in Step 3-1 of Fig. 1). Therefore, the floor area of the 17 building sub-types in each grid can be directly derived. Comparison between the modelled floor area with statistical yearbook recorded residential floor area for Shanghai will be performed in the Results and Discussion section.

With the building floor area known in each grid, to model the building stock value, another key component is the replacement value per square meter of each of the 17 buildings sub-types (namely factor *F5* in Step 3-2 of Fig. 1). Given the specialty/uniqueness of the building classification in this study, there is no official construction prices evaluated for the building types used here. Therefore, the unit construction price for each of the 17 building sub-types is derived (as listed in Table 3) by averaging the values given from different sources (e.g. 2015 China Construction Statistical Yearbook, the World Housing Encyclopedia, real-estate agency reports etc.). It should be noted that, due to the disparity of urbanization level, the actual construction price varies across urbanity levels and provinces in mainland China. Therefore, when applying the residential building stock model to target area for risk analysis, the construction price should be modified accordingly. In this study, the set of averaged unit construction prices for the 17 building sub-types listed in Table 3 is used mainly to initially evaluate the replacement value of the residential building stock in each geo-coded grid.

2.5: Step 4-Derive the replacement value of the 17 building sub-types in each grid.

As elaborated in Step 3, after multiplying the floor area with unit construction price, the replacement value of the 17 building sub-types within each grid can be evaluated. By summing up the replacement value of all the geo-coded grids, the overall residential building stock value in mainland China can also be derived (in RMB of 2015 current prices). It is worth to emphasize that in this residential building stock model, the term "building replacement value" is used, which refers to the amount that will be needed to rebuild a property exactly as it was prior to its destruction regardless of any depreciation due to its age, i.e. gross capital stock (Gunasekera et al., 2015).

3. Results and Discussion

3.1: Results----urbanity-level (urban/township/rural) based sum of modelled floor area and replacement value

Following the efforts of extensive data survey, collection and processing, with the modelling components and steps being explained in detail in Data Sources and Methodology section, a high-resolution (1km×1km) building stock model for mainland China targeted for future seismic risk assessment is established by disaggregating urbanity-level based census data into grid level. Since the census data are mainly related to residential buildings, the model developed is thus particularly for residential buildings. As listed in Table 4, the modelled residential building floor area and replacement value (unit: RMB, in 2015 current prices) in each grid are aggregated into urbanity level (urban/township/rural) for each province.

In 2015, the total modelled residential building floor area for mainland China reaches 42.64 billion m^2. By applying the same replacement price for the same building sub-type (in total 17) in all the urban/township/rural areas of the 31 provinces, the initially modelled residential building stock value in whole mainland China is approximately to be 77.6 trillion RMB (in 2015 current prices). It is clear that, like all other building stock, the Chinese building stock is a complicated economic, physical and social system (Yang and Kohler, 2008). The vacant building stock is also accounted for, thus is seen for places like New Ordos City. The economic disparity and geographic climatic diversity are widely spanned and the standardization in building construction also varies in different periods. Therefore, it is mainly for calculation convenience that this study applies the same unit construction price for all the provinces and all the urbanity levels. However, to improve accuracy in future seismic risk assessment, the unit construction price of specific building types in the target study area should be adjusted accordingly.

3.2: Discussion

In this study, the building stock model is established through the disaggregation of urbanity-level based 2010-census data into grid level by using 2015 GHS population density profile as the proxy. Due to the approximation and assumption made in this modelling process, the reasonability and consistency of the modelled results need to be cross validated. Due to the typical lack of official statistics on accumulated building stock value from the government (Wu et al., 2018), direct comparison of the modelled floor area and replacement value with that from census or statistical yearbooks for the whole mainland China is not available. Instead, the estimated stock value in previous studies is resorted to compare their modelled results with that in this study at provincial level.

3.2.1: Provincial-level based comparison between the modelled building value in this study and the net capital stock value estimated in Wu et al. (2014)

Previous studies on the capital stock estimation of mainland China mainly employed the perpetual inventory method (PIM), in which economy indicators e.g. gross fixed capital formation, total investment in fixed assets etc. were used. In general, these estimations are almost exclusively limited at national or provincial levels (Wu et al., 2014). Such coarse spatial resolution forms a major obstacle in applying the model in disaster loss estimation, due to the mismatch between the hazard extent and the administrative boundary. To better address this gap, Wu et al., (2014) estimated the net capital stock value (WKS) for 344 prefectures in mainland China by using the perpetual

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inventory method (PIM). In which, the WKS value (as listed in their Table A1) was calculated in 2012 current prices, with the depreciation of all exposed assets (i.e. residential and non-residential building structures, tools, machinery, equipment and infrastructure) being considered.

To better evaluate the reliability and consistency of the modelled results in this study, the estimated net capital stock value in Wu et al. (2014) for prefectures within the same province is aggregated into provincial level first, as shown in Table 4. The ratio between the modelled residential building stock value in this study (represented by "A") and the net capital stock value (represented by "C") in Wu et al. (2014) for each province is calculated in column "(A)/(C)" of Table 4 for straightforward comparison. The value of (A)/(C) varies within the range of **0.31-0.65**, which indicates the high consistency between the residential building replacement value modelled in this study in each province and the net capital stock value (for residential and non-residential buildings, infrastructure and other exposed elements) estimated in Wu et al. (2014), in spite of the differences in methodology and assumptions used in these two studies.

3.2.2: District-level based comparison between the modelled building floor area in this study and that recorded in statistical yearbook for Shanghai

A grid-level building stock model for Shanghai was developed in Wu et al. (2019), by disaggregating the district-level building floor area using building footprint map (extracted from high-resolution remote sensing data), combined with LandScan population density data as well as a financial appraisal of construction price according to building occupancy. However, Wu et al. (2019) did not separate residential floor area from non-residential floor area. Therefore, direct comparison of the modelled results from this study with their outputs is not available. On the other hand, yearbook records of the district-level residential and non-residential floor area, that were used in their study for model performance evaluation, turn out to be a good reference for this study to evaluate the modelled results at district-level, which can be extracted from Shanghai 2015 Statistical Yearbook.

To compare with the district-level residential floor area records in Shanghai statistical yearbook, the modelled floor area in each grid in Shanghai (Fig. 2) is aggregated into district level (as summarized in Table 5). As can be seen from Fig. 2 that grids with high floor area typically cluster in downtown area (including eight administrative districts, namely Yangpu, Hongkou, Zhabei, Putuo, Changning, Xuhui, Jing'an and Huangpu) and in Pudong district. This corresponds to the fact that these districts are the most developed in Shanghai. As can be further validated from the 3D-view of population distribution in panel (c) of Fig. 2, these districts also have the highest population density in Shanghai.

Table 5 gives a summary of the population in 2015 GHS population density profile, the modelled floor area (classified by storey classes) in this study, as well as the 2015 statistical yearbook recorded population and floor area for districts/counties in Shanghai. For more direct comparison, the initially modelled floor area (without adjustment) and the yearbook recorded floor area in each district of Shanghai are plotted in Fig. 3. The correlation between the initially modelled floor area and that recorded in yearbook turns out to be high, as indicated by the R^2 value (0.91). However, when it comes to the absolute floor area value, the total residential floor area modelled in Shanghai is around 808 km^2, while the yearbook recorded residential floor area is 611 km^2, which means the initially modelled results is overpredicted (around 1.3 multiples of the yearbook records). Therefore, additional

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efforts are required to adjust the initially modelled results, to make the modelled floor area in each district more reasonably distributed and to de-amplify the overprediction of the overall modelled results.

As discussed in the modelling process in the Data Sources and Methodology section, it is clear that the disaggregation of urbanity level floor area into each grid has not integrated the development disparity of districts/counties within the same province. Therefore, the initially modelled floor area will be firstly rectified by using the index of Uniform Construction Cost (UCC) to reflect the development inequality across districts in Shanghai, which has been used in previous studies (e.g. Gunasekera et al., 2015). The UCC index of each district in Shanghai is derived from the population and per capita GDP in 2015, which is defined as the triple root of the ratio between each district's GDP/capita and the average GDP/capita of Shanghai in 2015. As listed in Table 7, the higher the UCC index value, the more developed the corresponding district.

By multiplying the initially modelled floor area value with the UCC index in each district of Shanghai, the overall modelled floor area turns from 808 km^2 to 785 km^2. Although the overall floor area changes slightly, the application of UCC adjustment reallocates the floor area in each district, making it more consistent with the development level of each district. Meanwhile, compared with the recorded floor area of 611 km^2 for Shanghai in the yearbook, the UCC index adjusted floor area of 785 km^2 remains to be an obvious overprediction. Thus, de-amplification adjustment is needed as well. By checking the whole modelling process in Fig. 1 carefully, it is found out that the overprediction of the modelled floor area for Shanghai may be attributed to the use of amplification factor (*F2* in Step 1-3 of Fig. 1). *F2* is used to synchronously amplify the building related census data from year 2010 to 2015 level. Mathematically it is equal to the ratio between 2015 GHS population and 2010-census population for each urbanity level of each province. For example, the amplification factor *F2* in Shanghai is 1.33/1.34/1.29 for urban/township/rural level, respectively.

In reality, the increase of population in each urbanity level may not necessarily lead to the proportional increase of its residential floor area. Therefore, de-amplification of the initially modelled area for the whole Shanghai is attempted here. The derivation of the de-amplification factor of Shanghai is achieved by summarizing the product between the amplification factor of each urbanity level (*F2*) and its modelled floor area proportion. As shown in Table 6, the final de-amplification factor of Shanghai is 1.32.

After further applicating the de-amplification factor to the modelled floor area in Shanghai (which is 785 km^2 in total with UCC index adjustment), the final modelled floor area in each district of Shanghai is listed in Table 5. To better illustrate the difference between the initially modelled floor area and that adjusted by UCC index and de-amplification factor in each district of Shanghai, the comparison of modelled floor area (before and after adjustment) with statistical yearbook recorded floor area is plotted in Fig. 3. After adjusting the modelled floor area for each district of Shanghai with UCC index and de-amplification factor 1.32, for eight out of ten districts, the modelled floor area has a better match with yearbook records, except that Pudong district and Downtown are downwards deviating from the yearbook records after applying the de-amplification factor (Fig. 3). This is also easy to understand, since Pudong and Downtown are the most prosperous areas in Shanghai with increasing population inflow. Therefore, the increase of residential floor area in these two districts can be regarded as proportional to the increase of population. Thus, the de-amplification adjustment may not be appropriate for these two districts.

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However, in general, after the adjustment of initially modelled floor area by UCC index and the de-amplification factor, the overall modelled floor area in Shanghai turns to 594 km^2, only a 3% difference compared with the statistical record of 610.9 km^2 (Table 5). As can be more clearly seen from Fig. 3, the value of the correlation indicator R^2 improves from 0.91 (before adjustment) to 0.94 (after adjustment). This further indicates the reasonability of the adjustment made and the reliability of the modelled residential floor area in this study for Shanghai.

3.2.3: Application of the model to seismic loss estimation

Since the model developed in this study is mainly targeted for seismic risk analysis, the performance of the model is further evaluated by its application to the estimation of empirical loss in scenario earthquake.

The hazard component used for this loss assessment test is the macro-seismic intensity map of the 2008 Wenchuan Ms8.0 earthquake (Fig. 4), which was issued by the China Earthquake Administration (CEA) based on the post-earthquake field investigations. The vulnerability function used was the empirical loss function developed in Daniell (2014, Page 242) for mainland China. This empirical loss function was developed based on reported seismic damage and loss related to earthquakes that occurred in mainland China in the past few decades. Such information was retrieved through extensive collection of damage and loss records from journals, books, reports, conference proceedings and even newspapers, etc. Finally, based on the modelled residential building floor area in this study for Sichuan province and the unit construction price listed in Table 3, the estimated empirical loss to residential buildings caused by the recurrence of the Wenchuan Ms8.0 earthquake is around 432 billion RMB (in 2015 current price). The distribution of loss ratio, i.e., the ratio between the estimated loss and the residential building stock value in counties/districts of Sichuan Province that were damaged in the Wenchuan Ms8.0 earthquake is shown in Fig. 5.

In other reports and studies on the loss assessment of Wenchuan earthquake, e.g. in Yuan (2008), the estimated loss to residential buildings was around 170 billion RMB (in 2008 current price). The officially issued loss estimated by the Expert Panel of Earthquake Resistance and Disaster Relief (EPERDR, 2008) to residential buildings in Sichuan province was around 98.3-435.4 billion RMB, with the median around 212.32-247.25 billion RMB (in 2008 current price). It should be noted that in those studies, the unit construction price used for rural/urban/township buildings replacement was around 800-1500 RMB per square meter, which is 1/2.5-1/1.5 of the unit construction price used in this study as listed in Table 3. To reduce the gap in construction price used in this study and in previous studies, the estimated loss value (432 billion RMB) in this study is further divided by 1.5-2.5, so that the final loss estimate is around 144-288 billion RMB (in 2015 current price). Therefore, the estimated loss range, based on the buildings stock model developed in this study and the empirical loss function developed in Daniell (2014), is quite compatible with that given in previous studies. This compatibility further validates the robustness of our residential building stock model. Thus, the grid level building stock model developed in this study can be regarded as a reliable component input for further seismic risk assessment.

4. Conclusion

In this paper, a grid-level residential building stock model (in terms of floor area and replacement value) targeted for seismic risk analysis for mainland China is developed, by using 2015 GHS population density profile as the proxy and by disaggregating the urbanity level 2010-census data into 1km×1km scale for each province. To evaluate the model performance, the residential building stock value is compared with the net capital stock value estimated in Wu et al. (2014) using a perpetual inventory method at provincial level. The modelled stock value in these two studies are indeed quite consistent for all the 31 provinces in mainland China. Furthermore, district level comparison of the residential floor area developed in this study with records from the statistical yearbook of Shanghai is also conducted. It turns out that the floor area developed in this study is highly compatible with the floor area recorded in the yearbook of Shanghai. An adjustment to the modelled results is applied in order to more reasonably reflect the development disparities among districts within Shanghai. To further validate the performance of the model in seismic risk assessment, an empirical loss estimation for a recurrence of the 2008 Wenchuan M8.0 earthquake is performed. By reducing the gap in unit construction price used in this study and in previous studies, the overall estimated loss compares well with loss derived from damage reports based on field investigation. These results indicate the reliability of the geo-coded grid-level residential building stock model developed in this study. It is flexible for updates when more detailed census or statistics data are available, and it can be conveniently combined with hazard data and vulnerability information for risk assessment.

A limitation of this work is the focus on the residential building stock, as this exposure is accessible with the detailed census data. Although the damage to and the collapse of buildings is the main cause of fatalities and economic loss, damage to non-residential buildings (office, school, hospital, hotel, warehouse, factory, shop, cinema, etc.) as well as to life-line networks, infrastructures are not negligible. Therefore, future efforts should be made to estimate the stock value of non-residential buildings and infrastructures at risk. Furthermore, the replacement value developed in this study did not integrate the depreciation of the exposed buildings. Future work should target these deficiencies to better serve seismic risk analysis and loss mitigation strategies.

Data/Code Availability

1. 2015 Global Human Settlement (GHS) population density profile: http://data.europa.eu/89h/jrc-GHS-ghs_pop_gpw4_globe_r2015a.

2. 2010 China Sixth Population Census Tabulation: http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch.htm

3. 2015 China Statistical Yearbook On Construction: http://tongji.cnki.net/kns55/navi/YearBook.aspx?id=N2017020307&floor=1

4. 2015 Shanghai Statistics Yearbook: http://tjj.sh.gov.cn/html/sjfb/201701/1000201.html

5. Global Administrative Areas (GADM): www.gadm.org

6. An example illustrating the multi-variate equation solving process in Data Sources and Methodology section (the following two files are also available from the online supplementary document):

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(a) Input file: https://www.jianguoyun.com/p/DdOYRvoQgPb4Bhi-hdUB

(b) MATLAB script: https://www.jianguoyun.com/p/DcAageEQgPb4BhjHhdUB

Author contribution

DX conducted the data collection and preparation, results analysis, model validation and prepared the draft manuscript. JD guided the data collection and preparation process, developed the modelling methodology and performed the calculation and co-analysed the results. HT and FW supervised the project and provided advice and feedback in the process. All authors contributed to the revision of the manuscript.

Competing interests

The authors declare that they have no conflict of interests.

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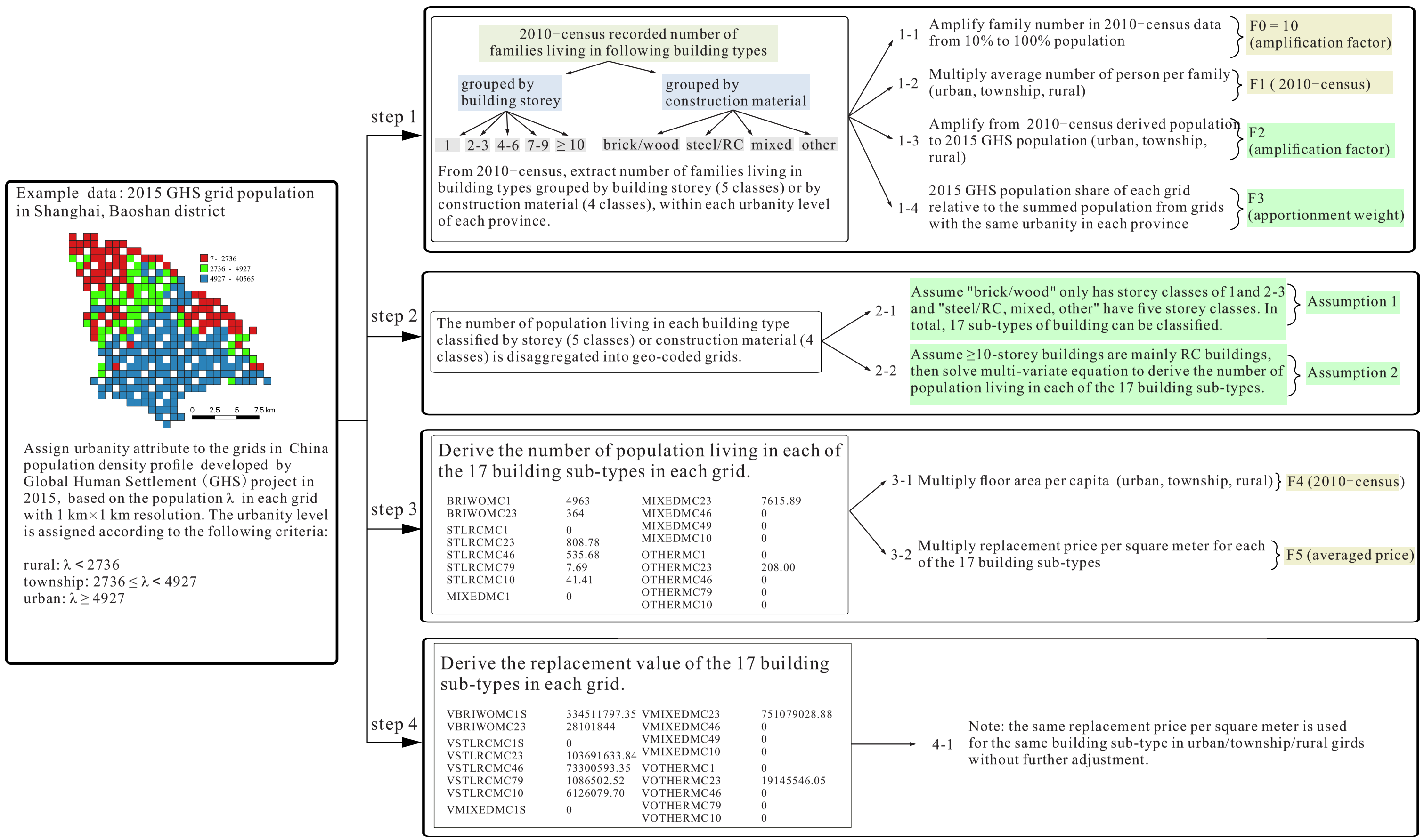

Figure 1: Flowchart of the residential building stock modelling process for mainland China. Detailed explanations of each component and step are given in the Data Sources and Methodology section.

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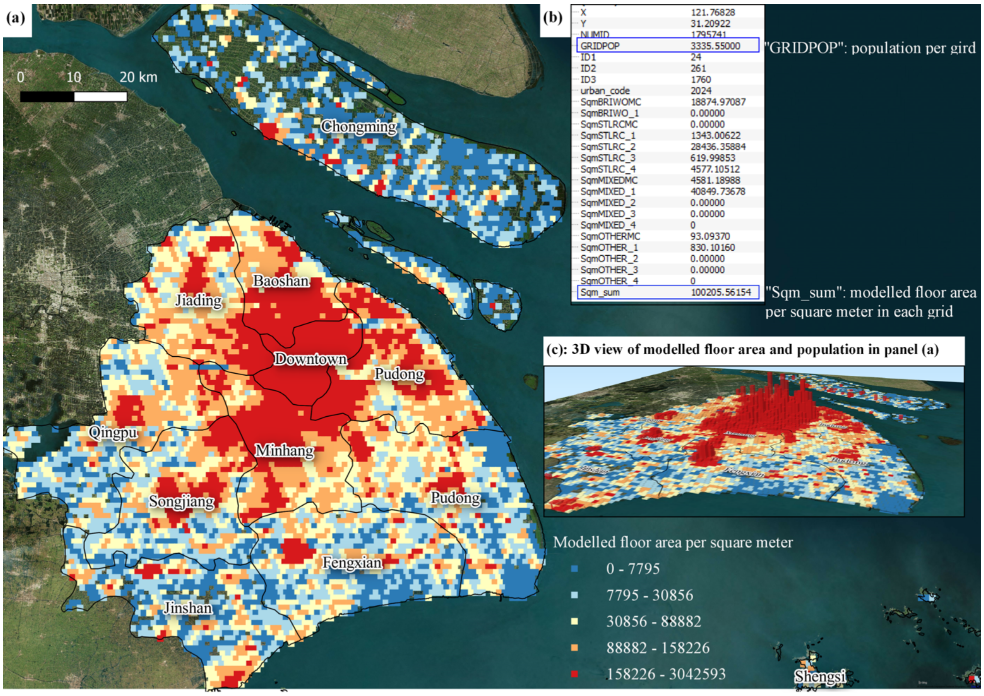

Figure 2. An example illustrating the modelled floor area for Shanghai: (a) the distribution of modelled floor area in each grid with resolution of 1km×1km; (b) This table shows the modelled floor area (unit: m^2) of the 17 building sub-types in one example grid, as well as the total population "GRIDPOP" and the total modelled floor area "Sqm_sum" in each grid; (c) the 3D view of the modelled floor area and the population distribution (the height of cuboid in each grid is proportional to its population density; the colour of each cuboid represents the modelled floor range). This figure is plotted using QGIS platform (https://qgis.org/en/site/) and the background aerial map is provided by Bing map service (Copyright: under the © Microsoft® BingTM Maps Platform APIs' terms of use, last updated May 2018).

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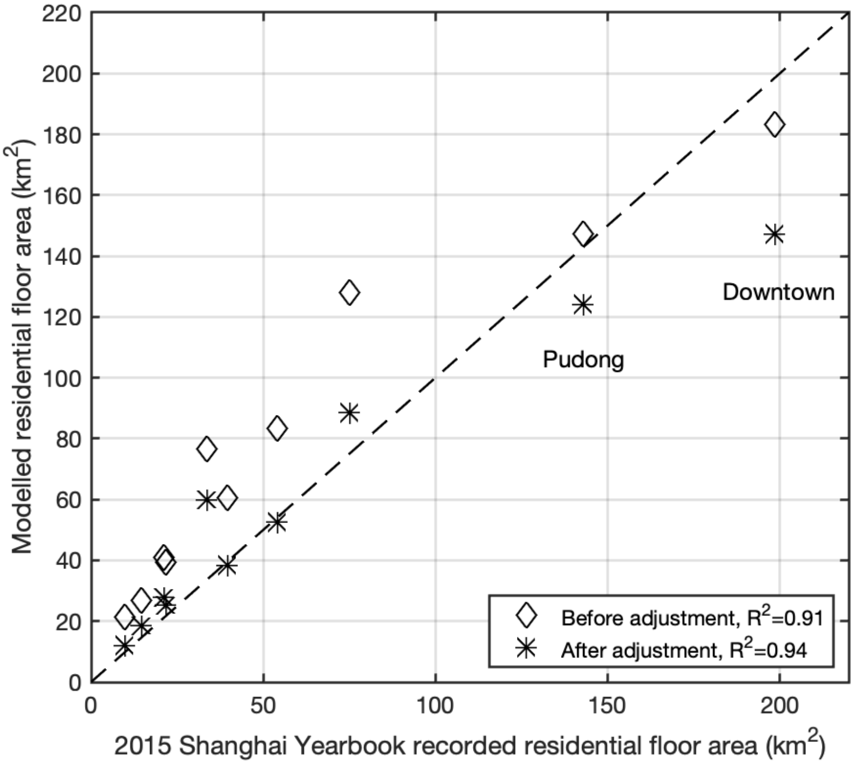

Figure 3: Comparison of the modelled floor area (before and after adjustment) with 2015 Shanghai Yearbook recorded floor area for each district of Shanghai.

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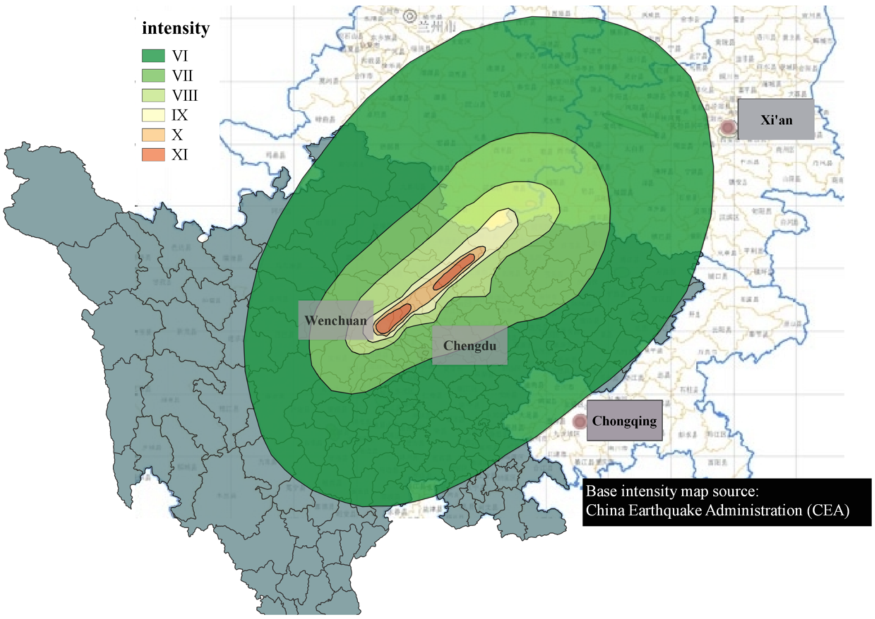

Figure 4. Macro-seismic intensity map of 2008 Wenchuan Ms8.0 earthquake, modified after the original map issued by China Earthquake Administration (CEA).

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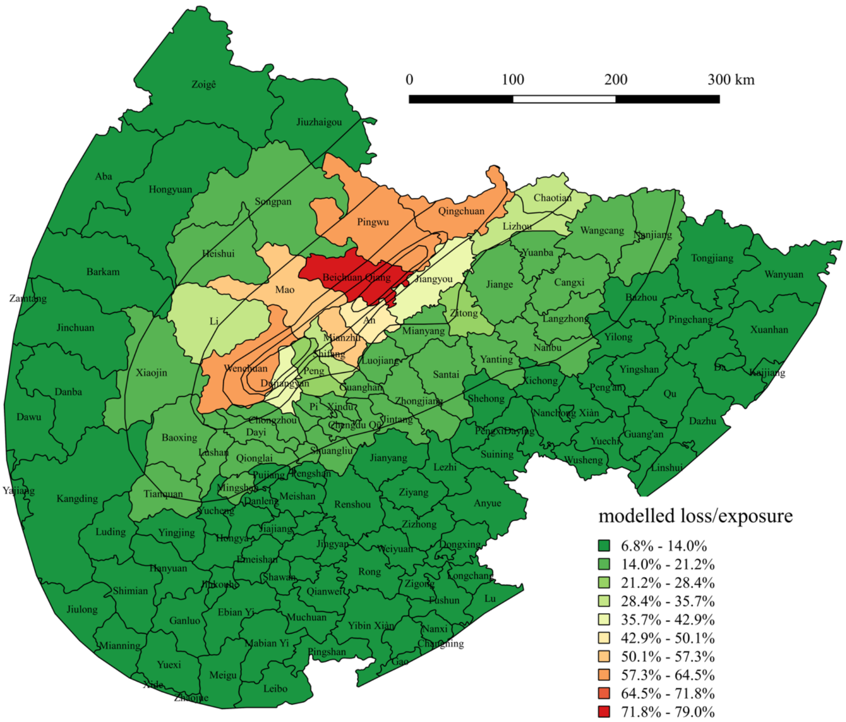

Figure 5. Distribution of estimated residential building loss ratio (the ratio between loss and exposed stock value) in affected districts/counties in Sichuan Province, by using the exact intensity map of the 2008 Wenchuan Ms8.0 earthquake as the hazard input. The black contours indicate the intensity levels within Sichuan Province (as shown in Figure 4).

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Table 1: Main data sources used in this study. Accesses to these data are provided in the Data/Code Availability section.

Data source	Data description	Resolution	Data location	Indicator in the text	Notes
2010 China Sixth Census Short Table	Overall population	urban/township/rural level for each of the 31 provinces/municipalities in mainland China; (the urbanity level in the census is defined according to the administrative belonging of the surveyed population)	Table 1-1a, 1-1b, 1-1c	N/A	Based on surveys of 100% of the population in mainland China
2010 China Sixth Census Long Table	Number of families living in buildings grouped by usage (residential, commercial, mixed)		Table 9-1a, 9-1b, 9-1c	N/A	Based on surveys of 10% of the overall population in mainland China
	Number of families dwelled in buildings grouped by storey number (1, 2-3, 4-6, 7-9, ≥10)				
	Number of families dwelled in buildings grouped by construction material (steel/RC, mixed, other, brick/wood)				
2010 China Sixth Census Short Table	Average population per family		Table 1-1a, 1-1b, 1-1c	D3 of Fig. 1	Based on surveys of 100% of the population in mainland China
	Average residential floor area per person (unit: square meter)		Table 1-14a, 1-14b, 1-14c	D4 of Fig. 1	
2015 GHS population density profile	provides the population density in each geo-coded grid	1km×1km	N/A	λ	The original resolution is 250m×250m and was resampled to 1km×1km
2015 Shanghai Statistics Yearbook	GDP and population in each district	District level	Page 495-545	N/A	To derive the uniform construction cost (UCC)
2015 China Construction Yearbook	Yearly construction value added in each province	Provincial level	Table 1-2	N/A	These data are used to evaluate modelled building stock value

Table 2: Residential building stock modelling related data extracted from the Tabulation of the 2010 Population Census of the People's Republic of China (abbreviated as "2010-census").

"Urbanity"+"0"+" Prov_ID"	Province	2015 GHS pop.	Floor area per capita	Person per family	Number of families grouped by occupancy			Number of families grouped by building height (storey class)					Number of families grouped by construction material				Amplification Factor (F2 in Fig.1, to amplify 2010-census data to 2015 level)
					living	commercial	mixed	1	2-3	4-6	7-9	≥10	steel/RC	mixed masonry	brick-wood	others	
								urban									
1001	Anhui	12162978	29.42	2.71	331730	9035	287	44093	82489	175486	20922	17775	135377	176462	26705	2221	1.32
1002	Beijing	18597540	27.81	2.40	517975	6482	988	127740	33290	193270	21919	148238	226367	212873	83192	2025	1.47
1003	Chongqing	8391462	29.77	2.65	258417	3956	247	17185	39448	39087	85383	81270	131656	112494	13433	4790	1.21
1004	Fujian	12699884	30.29	2.70	360721	13488	736	30557	97680	135725	79915	30332	213350	124702	23948	12209	1.25
1005	Gansu	5282457	26.69	2.68	160717	3134	107	24489	21076	75051	34161	9074	78731	66665	15057	3398	1.20
1006	Guangdong	56519993	26.37	2.63	1466895	34218	513	152601	299326	453172	412315	183699	748196	663772	76682	12463	1.43
1007	Guangxi	8478357	30.71	2.93	238044	5912	264	26305	53876	99335	52485	11955	86601	138730	16271	2354	1.18
1008	Guizhou	5485811	25.94	2.82	157713	5141	19	17373	38055	50766	49256	7404	78055	75834	7703	1262	1.19
1009	Hainan	2327452	25.42	3.17	56383	1602	68	9674	14288	13787	13124	7112	41510	10814	4948	713	1.26
1010	Hebei	14836541	30.10	2.95	419978	3950	96	100741	42944	230919	29889	19435	155581	211716	54745	1886	1.19
1011	Heilongjiang	14367419	23.72	2.58	455996	6911	418	122051	20020	130862	173283	16691	163427	188650	104208	6622	1.20
1012	Henan	18527056	34.02	3.05	521036	7612	215	79535	122569	244091	64920	17533	190648	307902	28268	1830	1.15
1013	Hubei	17537483	33.22	2.82	502439	12733	349	40937	132838	179474	126270	35653	180316	298109	33900	2847	1.21
1014	Hunan	12911981	33.45	2.89	358447	9813	501	32935	92165	160007	62887	20266	132713	201615	31404	2528	1.21
1015	Jiangsu	30857658	33.86	2.81	876264	14961	802	129293	224580	412115	65052	60185	325288	469388	92721	3828	1.23
1016	Jiangxi	7844695	29.76	3.19	201690	3594	201	17052	46727	85663	48457	7385	111658	76679	15396	1551	1.20
1017	Jilin	10270924	25.21	2.62	329782	4910	1777	59861	13029	149906	96067	15829	175788	108325	48852	1727	1.17
1018	Liaoning	22172958	25.76	2.57	768884	7122	843	111439	28046	366106	211530	58885	321935	381031	71386	1654	1.11
1019	Inner Mongolia	8302698	24.86	2.67	251738	6951	631	84432	24977	133932	11690	3658	105902	87092	61924	3771	1.20
1020	Ningxia	2215109	28.38	2.71	64336	1829	29	10922	7958	44770	1313	1202	24606	34483	6352	724	1.23
1021	Qinghai	1470242	27.77	2.74	41342	1229	62	4877	8035	20737	6292	2630	13527	26113	2415	516	1.26
1022	Shaanxi	9021036	28.81	2.70	269044	4820	362	33723	56478	122687	37356	23620	89287	173753	8694	2130	1.22
1023	Shandong	28921044	32.41	2.80	855282	15616	242	252471	88326	432226	67205	30670	348873	356038	161295	4692	1.19
1024	Shanghai	20557127	25.11	2.52	604654	9991	928	60506	116799	304794	27780	104766	268377	249438	93734	3096	1.33
1025	Shanxi	9837996	25.77	2.88	282847	4319	87	53815	47879	157087	18683	9702	90187	163209	29124	4646	1.19
1026	Sichuan	15732199	30.70	2.67	499024	9628	630	47158	79975	198299	136824	46396	218827	247875	34088	7862	1.16
1027	Tianjin	10012251	25.51	2.65	237060	2606	167	34902	12083	143755	28570	20356	58333	156521	23467	1345	1.58
1028	Xinjiang	6578245	28.00	2.56	201621	2686	84	32261	24343	129144	12124	6435	88699	94628	18420	2560	1.26
1029	Tibet	289534	31.81	2.45	8394	973	7	2930	4798	1580	47	12	5449	2227	1020	671	1.26
1030	Yunnan	6531449	31.27	2.59	200602	7122	172	21262	45555	93027	36704	11176	102015	85386	13317	7006	1.21
1031	Zhejiang	21732071	30.97	2.54	675858	19305	774	80859	193447	332899	50666	37292	220048	393843	74559	6713	1.23
								township									

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2001	Anhui	13372970	32.20	2.95	355306	19130	477	144219	160370	67744	1426	677	95625	182264	91921	4626	1.21
2002	Beijing	1548053	33.20	2.52	41959	1129	143	21808	2812	16414	710	1344	6224	20550	15964	350	1.42
2003	Chongqing	6393138	34.91	2.73	187287	7816	357	35957	71385	40448	41156	6157	46425	112018	23805	12855	1.20
2004	Fujian	8616342	37.67	3.09	224647	11851	318	44154	105240	65529	18822	2753	100650	83984	28551	23313	1.18
2005	Gansu	3949838	25.92	3.17	101071	5160	124	58128	13450	30226	4198	229	31721	30839	34944	8727	1.17
2006	Guangdong	17954335	26.41	3.52	357650	15136	348	119634	161452	60743	27235	3722	124661	175520	63890	8715	1.37
2007	Guangxi	10216390	34.43	3.34	264485	12263	480	94666	111560	58971	11002	549	53729	175149	42500	5370	1.10
2008	Guizhou	6142030	28.39	3.12	159970	12522	41	65929	60006	34332	11785	440	44016	89287	28725	10464	1.14
2009	Hainan	1986929	23.78	3.42	45035	2592	51	26889	15458	4359	607	314	19912	12356	14449	910	1.22
2010	Hebei	17723090	30.74	3.40	454034	12232	203	338450	45232	73026	3484	6074	90952	165751	204531	5032	1.12
2011	Heilongjiang	7326077	22.67	2.63	230438	7764	526	152211	13711	54825	16851	604	26869	70838	130084	10411	1.17
2012	Henan	18079108	32.04	3.60	435993	14307	304	242151	151413	53669	2676	391	91696	240373	114219	4012	1.11
2013	Hubei	10287748	38.10	3.12	267951	11284	318	65151	136106	59020	18152	806	75159	150951	47125	6000	1.18
2014	Hunan	15928705	36.74	3.18	413160	16084	1397	107304	216464	90305	12926	2245	103618	225168	92116	8342	1.16
2015	Jiangsu	17599234	39.53	3.00	493818	16021	436	194665	224247	86379	2299	2249	99148	264939	142526	3226	1.15
2016	Jiangxi	12539807	33.57	3.54	283781	10796	1125	57795	138466	80093	17102	1121	144491	98662	45425	5999	1.20
2017	Jilin	4483838	22.51	2.70	139477	4710	1966	90313	10161	37025	6460	228	34567	30467	73754	5399	1.14
2018	Liaoning	5202389	26.23	2.75	168663	5618	94	100064	11565	51923	9229	1500	51280	52098	69815	1088	1.08
2019	Inner Mongolia	5916056	24.38	2.74	172725	9637	1622	124351	14566	41832	1422	191	43195	35332	90983	12852	1.17
2020	Ningxia	1035570	24.82	3.14	25273	1397	58	16542	2590	7308	176	54	6140	7109	12255	1166	1.23
2021	Qinghai	1234007	21.94	3.06	28364	1806	1694	15491	4641	9622	386	30	8482	9814	8928	2946	1.27
2022	Shaanxi	8393227	28.85	3.05	218969	10349	295	103810	63776	53427	6133	2172	61288	115983	30075	21972	1.20
2023	Shandong	19633228	32.14	3.03	555539	16773	117	412345	53861	102936	2235	935	105549	177664	274908	14191	1.13
2024	Shanghai	3396024	30.25	2.45	100049	3066	715	24233	44272	29262	638	4710	35992	46750	19423	950	1.34
2025	Shanxi	8095334	25.43	3.24	208837	7124	292	128133	41454	42626	2929	819	49930	87194	66418	12419	1.16
2026	Sichuan	16239393	34.47	2.80	494678	24545	2048	133695	170345	141458	64579	9146	144800	259633	80423	34367	1.11
2027	Tianjin	1604748	29.64	2.98	36626	688	6	20978	1965	12727	559	1085	5896	13066	18217	135	1.44
2028	Xinjiang	3536191	26.04	2.75	95090	2368	50	57285	7087	32598	301	187	31109	21827	34576	9946	1.32
2029	Tibet	434071	33.52	2.89	10835	1334	69	5712	5333	1058	39	27	5633	2406	2961	1169	1.23
2030	Yunnan	9948973	30.04	3.29	249892	15089	538	95990	113777	49076	5598	540	85728	73181	58444	47628	1.14
2031	Zhejiang	14032915	38.53	2.66	435571	17019	321	78393	215994	143891	9590	4722	88524	262572	92204	9290	1.16
rural																	
3001	Anhui	33868749	34.04	3.12	972114	12697	1032	594442	384935	5062	259	113	122416	440296	399437	22662	1.10
3002	Beijing	3290554	35.39	2.76	85494	2139	89	81788	2698	2877	93	177	2991	19546	63298	1798	1.36
3003	Chongqing	13097499	42.04	2.72	436237	8496	810	215548	219389	6337	3076	383	34275	160849	146892	102717	1.08
3004	Fujian	16023424	41.24	3.16	447940	13851	615	152099	279696	27946	1860	190	105558	152003	108638	95592	1.10
3005	Gansu	16457361	21.94	3.89	444734	2789	233	434394	12043	911	94	81	23583	50990	233241	139709	0.94
3006	Guangdong	38073367	25.99	3.74	825588	7932	862	473821	328499	27016	3542	642	168179	388958	244088	32295	1.22
3007	Guangxi	28020960	28.82	3.47	788492	7837	834	494076	294396	7474	300	83	100152	424443	210891	60843	1.01
3008	Guizhou	22795976	27.92	3.29	657275	13176	244	526145	137494	5485	1206	121	80232	208026	247780	134413	1.03
3009	Hainan	4368909	21.29	3.63	109378	771	69	101212	8248	437	217	35	22309	16584	68949	2307	1.09
3010	Hebei	41534503	30.09	3.50	1138877	6755	525	1108487	32754	3591	510	290	65563	351042	689663	39364	1.04
3011	Heilongjiang	17284909	20.92	3.19	472849	3926	1647	469755	3174	2668	1148	30	5933	44163	339849	86830	1.13
3012	Henan	58426898	32.23	3.58	1593259	18790	715	1263614	341472	6231	554	178	170146	778487	632719	30697	1.01
3013	Hubei	28165214	38.64	3.40	805308	11381	807	395220	405959	12191	2267	1052	87280	373421	286599	69389	1.01
3014	Hunan	37755133	34.27	3.54	1008324	9900	2170	496152	516168	5569	262	73	113888	408562	427367	68407	1.05

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3015	Jiangsu	32006376	42.35	3.03	978352	13096	999	526012	444382	17344	893	2817	77218	494838	411206	8186	1.06
3016	Jiangxi	26204945	33.81	3.86	627420	6578	1410	251425	373710	8390	355	118	184327	209487	198186	41998	1.07
3017	Jilin	12897767	20.98	3.35	353543	2220	2523	347297	3170	4561	676	59	11283	35524	274007	34949	1.07
3018	Liaoning	16672483	25.95	3.12	519784	3994	237	512930	6643	3709	390	106	31856	123657	360371	7894	1.02
3019	Inner Mongolia	11385344	22.17	2.97	337168	4773	1167	331674	6301	3644	77	245	10616	34647	206674	90004	1.12
3020	Ningxia	3527454	22.12	3.54	86461	1371	35	80927	1965	4863	64	13	4944	9056	60381	13451	1.13
3021	Qinghai	3342860	18.51	4.06	71842	604	1521	69459	2789	181	7	10	2675	9718	36221	23832	1.11
3022	Shaanxi	20689727	31.22	3.54	572916	6711	497	481090	94599	3360	348	230	60338	235474	142395	141420	1.01
3023	Shandong	49116344	31.95	3.07	1549890	8748	182	1511164	40165	6807	399	103	77610	400711	1025247	55070	1.03
3024	Shanghai	2871449	38.83	2.37	90972	1752	1153	31644	57352	3415	49	264	8884	48551	33963	1326	1.29
3025	Shanxi	19386995	25.09	3.44	521669	4921	593	481296	38553	6348	290	103	34053	138101	243316	111120	1.07
3026	Sichuan	47518958	36.63	3.10	1625052	36122	3253	1067677	574735	16573	1425	764	147168	513785	611594	388627	0.92
3027	Tianjin	3007476	25.95	3.21	78318	570	30	74498	686	3345	110	249	2325	7772	68306	485	1.19
3028	Xinjiang	13521011	22.35	3.55	314397	2226	115	309505	2663	4345	82	28	11730	36704	207565	60624	1.20
3029	Tibet	2468309	27.55	4.95	44816	1260	718	27819	17858	360	26	13	2594	5152	23631	14699	1.07
3030	Yunnan	30987983	25.61	3.89	756974	10742	1276	461191	296513	6950	2470	592	68863	112129	239753	346971	1.04
3031	Zhejiang	22254831	49.12	2.67	740469	17587	807	152558	544733	58732	1649	384	60829	419761	236627	40839	1.10

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Table 3: Averaged construction price per square meter for each of the 17 building sub-types used in this study to estimate the building stock value in mainland China.

Construction material	Storey class	Building type abbreviation	Construction price (RMB/m^2 in 2015 current price)
brick/wood	1	BRIWOMC1	2050
	2-3	BRIWOMC23	2350
steel/RC	1	STLRCMC1	3700
	2-3	STLRCMC23	3900
	4-6	STLRCMC46	4100
	7-9	STLRCMC79	4300
	≥10	STLRCMC10	4500
mixed	1	MIXEDMC1	2800
	2-3	MIXEDMC23	3000
	4-6	MIXEDMC46	3200
	7-9	MIXEDMC79	3400
	≥10	MIXEDMC10	3600
others	1	OTHERMC1	2600
	2-3	OTHERMC23	2800
	4-6	OTHERMC46	3000
	7-9	OTHERMC79	3200
	≥10	OTHERMC10	3400

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Table 4: Modelled residential building floor area and replacement value for urban/township/rural area of 31 provinces/municipalities in mainland China and comparison with net capital stock value estimated in Wu et al. (2014) using perpetual inventory method (in this table, scientific notation is used to represent the large numbers).

Prov_ID	Province	Initially modelled residential floor area (m^2)			**(A)**: Initially modelled **residential** building stock replacement value (RMB in 2015 current price)			**(C)**: Net capital stock value modelled in Wu et al. (2014, RMB in 2012 current price)	**(A)/(C)**
		urban	township	rural	urban	township	rural		
01	Anhui	3.57E+08	4.30E+08	1.15E+09	5.08E+11	4.97E+11	1.08E+12	3.86E+12	0.54
02	Beijing	5.16E+08	5.13E+07	1.16E+08	1.92E+12	1.48E+11	2.22E+11	3.85E+12	0.59
03	Chongqing	2.50E+08	2.23E+08	5.50E+08	5.63E+11	4.29E+11	8.25E+11	2.98E+12	0.61
04	Fujian	1.40E+08	2.46E+08	1.07E+09	3.61E+11	5.14E+11	2.02E+12	4.73E+12	0.61
05	Gansu	1.41E+08	1.02E+08	3.61E+08	2.31E+11	1.14E+11	2.71E+11	1.56E+12	0.39
06	Guangdong	1.11E+09	4.16E+08	1.40E+09	2.97E+12	8.05E+11	1.74E+12	1.07E+13	0.52
07	Guangxi	2.27E+08	2.94E+08	8.84E+08	5.42E+11	5.78E+11	1.29E+12	4.74E+12	0.51
08	Guizhou	1.42E+08	1.74E+08	6.36E+08	2.19E+11	1.98E+11	4.88E+11	2.08E+12	0.44
09	Hainan	1.82E+07	2.37E+07	1.43E+08	3.98E+10	3.87E+10	1.63E+11	7.86E+11	0.31
10	Hebei	3.90E+08	5.16E+08	1.33E+09	7.75E+11	8.23E+11	1.56E+12	6.82E+12	0.46
11	Heilongjiang	3.37E+08	1.65E+08	3.64E+08	8.39E+11	2.56E+11	3.68E+11	3.19E+12	0.46
12	Henan	6.30E+08	5.79E+08	1.88E+09	1.12E+12	1.02E+12	2.56E+12	9.30E+12	0.51
13	Hubei	5.82E+08	3.92E+08	1.09E+09	1.30E+12	6.09E+11	1.40E+12	5.44E+12	0.61
14	Hunan	4.31E+08	5.83E+08	1.29E+09	7.75E+11	7.86E+11	1.36E+12	5.22E+12	0.56
15	Jiangsu	8.27E+08	5.98E+08	1.73E+09	2.72E+12	1.67E+12	3.91E+12	1.27E+13	0.65
16	Jiangxi	2.33E+08	4.20E+08	8.84E+08	3.85E+11	5.35E+11	8.45E+11	2.93E+12	0.60
17	Jilin	2.48E+08	9.70E+07	2.79E+08	1.04E+12	2.60E+11	5.10E+11	4.52E+12	0.40
18	Liaoning	4.35E+08	1.14E+08	5.86E+08	1.68E+12	2.92E+11	1.07E+12	6.82E+12	0.45
19	Inner Mongolia	2.01E+08	1.38E+08	2.60E+08	1.20E+12	4.73E+11	5.94E+11	5.39E+12	0.42
20	Ningxia Hui	6.27E+07	2.57E+07	7.80E+07	1.83E+11	5.62E+10	1.22E+11	8.53E+11	0.42
21	Qinghai	4.07E+07	2.56E+07	6.07E+07	1.26E+11	5.47E+10	8.76E+10	6.26E+11	0.43
22	Shaanxi	2.59E+08	2.42E+08	6.46E+08	7.19E+11	5.22E+11	9.62E+11	4.25E+12	0.52
23	Shandong	7.49E+08	5.27E+08	1.85E+09	1.74E+12	1.05E+12	3.23E+12	1.32E+13	0.46
24	Shanghai	4.70E+08	1.10E+08	1.68E+08	1.99E+12	3.68E+11	3.92E+11	4.57E+12	0.60

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25	Shanxi	2.53E+08	2.06E+08	4.86E+08	6.58E+11	3.61E+11	5.89E+11	3.27E+12	0.49
26	Sichuan	4.72E+08	5.51E+08	1.76E+09	7.95E+11	7.67E+11	1.81E+12	5.77E+12	0.58
27	Tianjin	2.19E+08	4.45E+07	1.18E+08	1.43E+12	1.90E+11	3.27E+11	3.88E+12	0.50
28	Xinjiang	1.81E+08	8.60E+07	3.10E+08	5.37E+11	1.96E+11	2.92E+11	2.19E+12	0.47
29	Tibet	8.73E+06	1.22E+07	6.92E+07	2.41E+10	3.06E+10	8.57E+10	3.37E+11	0.42
30	Yunnan	1.77E+08	2.33E+08	8.66E+08	2.83E+11	3.30E+11	8.14E+11	3.27E+12	0.44
31	Zhejiang	4.56E+08	4.10E+08	1.59E+09	1.20E+12	8.98E+11	2.84E+12	7.80E+12	0.63
In total:		1.06E+10	8.04E+09	2.40E+10	2.89E+13	1.49E+13	3.38E+13	1.48E+14	0.53

Note: (a) In this study, for each of the 17 building sub-types in each grid of urban/township/rural level in each province/municipality, the same unit construction price is used; (b) The modelled floor area and replacement value in this study are particularly for residential buildings; (c) The net capital stock value estimated in Wu et al. (2014) refers to the depreciated asset value of residential, non-residential buildings, and infrastructure as well; (d) The building construction price used in this study and that in Wu et al. (2014) are not equal.

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Table 5: Comparison of modelled floor area with Shanghai Statistical Yearbook records in 2015 (in this table, scientific notation is used to represent the large numbers).

District	Initially modelled population and floor area (km^2)								Adjustment factor		Adjusted floor area (km^2)	2015 Shanghai Statistical Yearbook records			
	2015 GHS (pop1)	pop1 (%)	1	2-3	4-6	7-9	≥10	Sum of floor area in all storey classes	**UCC**	**De-amp. factor**		floor area difference (%)	residential floor area (km^2)	Recorded population (pop2)	pop2 (%)
Baoshan	2.70E+06	10%	12.7	23.6	33.5	2.8	10.8	83.3	0.83	**1.32**	52.4	-3%	54	2.02E+06	8%
Chongming	6.67E+05	3%	7.0	12.6	1.4	0.0	0.2	21.3	0.74		12.0	23%	9.7	7.02E+05	3%
Fengxian	1.26E+06	5%	8.6	15.8	10.9	0.8	3.2	39.4	0.85		25.2	17%	21.6	1.17E+06	5%
Jiading	2.49E+06	9%	12.1	22.2	30.2	2.5	9.7	76.7	1.03		60.0	78%	33.6	1.57E+06	6%
Jinshan	8.54E+05	3%	5.7	10.5	7.8	0.5	2.2	26.7	0.91		18.4	25%	14.7	7.97E+05	3%
Minhang	4.20E+06	16%	15.3	29.0	58.9	5.1	19.6	127.9	0.92		88.6	18%	75.2	2.54E+06	10%
Pudong	4.74E+06	18%	27.6	51.1	49.5	3.9	15.2	147.2	1.11		124.0	-13%	142.9	5.45E+06	22%
Qingpu	1.33E+06	5%	8.5	15.6	12.5	0.9	3.6	41.1	0.90		27.9	32%	21.2	1.21E+06	5%
Songjiang	1.96E+06	7%	9.7	18.0	23.4	1.9	7.4	60.5	0.84		38.2	-3%	39.5	1.76E+06	7%
Downtown	5.99E+06	23%	22.9	43.3	82.5	7.2	27.5	183.4	1.06		147.3	-26%	198.5	7.05E+06	29%
	Sum: 2.62E+07							Sum: 807.5			Sum: 594.0	**-3%**	Sum: 610.9	Sum: 2.43E+07	

Note: In "Adjustment factor" column, "**UCC**" is the abbreviation of Uniform Construction Price, derived in Table 7 and used to adjust the development disparity in districts of Shanghai; "**De-amp. factor**" is the averaged de-amplification factor, derived in Table 6 and used to adjust the amplification of population from 2010 census to 2015 GHS population; "**Downtown**" area includes eight administrative districts of Shanghai, namely Yangpu, Hongkou, Zhabei, Putuo, Changning, Xuhui, Jing'an and Huangpu.

Table 6: Derivation process of the de-amplification factor "1.32" in Table 5.

Shanghai urbanity	Modelled floor area (km^2), without adjustment	Ratio (%)	Amp. Factor from 2010 census to 2015 GHS population	De-amp. factor
1024	469.6	63%	1.33	**1.32**
2024	110.4	15%	1.34	
3024	167.8	22%	1.29	

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Table 7: Derivation of Uniform Construction Cost (UCC) in Table 5 from Shanghai 2015 Statistical Yearbook, to reflect the development disparity among districts of Shanghai (in this table, scientific notation is used to represent the large numbers).

District	Population	District GDP	GDP/capita	UCC
Baoshan	202400	1.10E+11	54147	0.83
Chongming	70160	2.72E+10	38791	0.74
Fengxian	116760	6.68E+10	57246	0.85
Jiading	156620	1.63E+11	104084	1.03
Jinshan	79710	5.70E+10	71509	0.91
Minhang	253950	1.84E+11	72603	0.92
Pudong	545120	7.11E+11	130414	1.11
Qingpu	120830	8.27E+10	68476	0.90
Songjiang	175590	9.69E+10	55212	0.84
Downtown	704540	7.96E+11	113012	1.06
	sum: 2425680	sum: 2.29E+12	average: 94607	

Note: “Downtown” area includes eight districts of Shanghai located in the downtown area, namely Yangpu, Hongkou, Zhabei, Putuo, Changning, Xuhui, Jingan and Huangpu.

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Appendix

Table A1: The population thresholds used to divide the grids in 2015 GHS population density profile into urban/township/rural level.

Province	Province ID	Population of each urbanity level in 2010-census				Population share (%)			Population threshold (PT)	
		urban	township	rural	sum	urban	township	rural	**PT1** (urban/township)	**PT2** (township/rural)
Anhui	1	12182587	13394530	33923351	59500468	20.47%	22.51%	57.01%	13991	6908
Beijing	2	15563215	1295477	2753676	19612368	79.35%	6.61%	14.04%	2709	1784
Chongqing	3	8681611	6614192	13550367	28846170	30.10%	22.93%	46.97%	11194	5415
Fujian	4	12548384	8513556	15832277	36894217	34.01%	23.08%	42.91%	6177	2621
Gansu	5	5258935	3932250	16384078	25575263	20.56%	15.38%	64.06%	15175	9350
Guangdong	6	52388382	16641873	35290204	104320459	50.22%	15.95%	33.83%	4427	2521
Guangxi	7	8352777	10065066	27605918	46023761	18.15%	21.87%	59.98%	11711	5087
Guizhou	8	5537562	6199971	23011023	34748556	15.94%	17.84%	66.22%	18126	10384
Hainan	9	2324288	1984228	4362969	8671485	26.80%	22.88%	50.31%	8098	3658
Hebei	10	14388021	17187307	40278882	71854210	20.02%	23.92%	56.06%	5670	2402
Heilongjiang	11	14122516	7201199	16990276	38313991	36.86%	18.80%	44.34%	3845	1483
Henan	12	18331493	17888274	57810172	94029939	19.50%	19.02%	61.48%	15203	8451
Hubei	13	17928160	10516925	28792642	57237727	31.32%	18.37%	50.30%	11667	6345
Hunan	14	12738442	15714621	37247699	65700762	19.39%	23.92%	56.69%	13563	5881
Jiangsu	15	30166466	17205022	31289453	78660941	38.35%	21.87%	39.78%	6554	3341
Jiangxi	16	7504291	11995669	25067837	44567797	16.84%	26.92%	56.25%	11309	3403
Jilin	17	10196745	4451454	12804616	27452815	37.14%	16.21%	46.64%	6150	2849
Liaoning	18	22021184	5166779	16558360	43746323	50.34%	11.81%	37.85%	3486	1874
Inner Mongolia	19	8011564	5708610	10986117	24706291	32.43%	23.11%	44.47%	11152	5041
Ningxia	20	2059295	962727	3279328	6301350	32.68%	15.28%	52.04%	11659	7624
Qinghai	21	1368033	1148221	3110469	5626723	24.31%	20.41%	55.28%	11850	5088
Shaanxi	22	8837175	8222162	20268042	37327379	23.67%	22.03%	54.30%	13716	6862
Shandong	23	28364984	19255743	48171992	95792719	29.61%	20.10%	50.29%	6587	3373
Shanghai	24	17640842	2914256	2464098	23019196	76.64%	12.66%	10.70%	4927	2736
Shanxi	25	9414053	7746486	18551562	35712101	26.36%	21.69%	51.95%	8763	3873
Sichuan	26	15915660	16428768	48073100	80417528	19.79%	20.43%	59.78%	14668	8133
Tianjin	27	8858126	1419767	2660800	12938693	68.46%	10.97%	20.56%	3141	1868
Xinjiang	28	6071803	3263949	12480063	21815815	27.83%	14.96%	57.21%	10473	3618
Tibet	29	272322	408267	2321576	3002165	9.07%	13.60%	77.33%	9751	4483
Yunnan	30	6324830	9634242	30007694	45966766	13.76%	20.96%	65.28%	18128	8118
Zhejiang	31	20386294	13163915	20876682	54426891	37.46%	24.19%	38.36%	5594	2504

Note: For each province, **PT1** and **PT2** are two population thresholds used to assign the grids in 2015 GHS population density profile with urban, township and rural attributes, according to the population density λ in each grid with 1km×1km resolution . The detailed criteria are that: if $\lambda \geqslant PT1$, the grid is assigned as **urban**; if $PT1>\lambda \geqslant PT2$, **township**; *if* $\lambda<PT2$, **rural**.