A Probabilistic Dynamic Material Flow Analysis Model for Chinese Urban Housing Stock

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Summary

The stock-driven dynamic material flow analysis (MFA) model is one of the prevalent tools to investigate the evolution and related material metabolism of the building stock. There exists substantial uncertainty inherent to input parameters of the stock-driven dynamic building stock MFA model, which has not been comprehensively evaluated yet. In this study, a probabilistic, stock-driven dynamic MFA model is established and China's urban housing stock is selected as the empirical case. This probabilistic dynamic MFA model has the ability to depict the future evolution pathway of China's housing stock and capture uncertainties in its material stock, inflow, and outflow. By means of probabilistic methods, a detailed and transparent estimation of China's housing stock and its material metabolism behavior is presented. Under a scenario with a saturation level of the population, urbanization, and living space, the median value of the urban housing stock area, newly completed area, and demolished area would peak at around 49, 2.2, and 2.2 billion square meters, respectively. The corresponding material stock and flows are 79, 3.5, and 3.3 billion tonnes, respectively. Uncertainties regarding housing stock and its material stock and flows are non-negligible. Relative uncertainties of the material stock and flows are above 50%. The uncertainty importance analysis demonstrates that the material intensity and the total population are major contributions to the uncertainty. Policy makers in the housing sector should consider the material efficiency as an essential policy to mitigate material flows of the urban building stock and to lower the risk of policy failures.

Introduction

The building sector plays a central role in consumption of resources and energy in many countries (Gallardo et al. 2014). The accumulation of building stock has given rise to resource extraction and waste emissions (Kohler and Yang 2007; Wiedenhofer et al. 2015). A crucial issue for environmental policy makers in the building sector is to obtain a future picture of the anticipated environmental problems and to take timely action (Van der Voet et al. 2002). The application of dynamic models can serve to evaluate the quantity of materials stored in the building stock (Kapur et al. 2008). Estimating the input and output flows derived from the material metabolism of the building stock can provide insights for decision makers to deal with concomitant environmental problems (Brattebø et al. 2009).

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Considering the long lifetime characteristic of the building stock, several researchers have pioneered the introduction of time-lag effects of material inflow in the model to predict the temporal behavior of building stocks in various countries. Müller (2006) developed an archetypal dynamic material flow analysis (MFA) model and applied this model to forecast resource demands and waste emissions of the housing stock in the Netherlands during the period of 1900–2100. Taking advantage of this dynamic MFA model, the Norwegian residential housing stock is estimated from 1900 to 2100 and its corresponding concrete and wood accumulated in it are simulated (Bergsdal et al. 2007). On the basis of results of analysis of historical Norwegian residential stocks, the direct and indirect energy flows have been estimated (Sandberg et al. 2011). Further, the life cycle appraisal for the energy and carbon flows of prospective building stocks in Norway toward 2050 is carried out (Sandberg and Brattebø 2012). In light of the compatibility of the dynamic MFA model, the current and future flows of polychlorinated biphenyls in Norway are investigated as well (Bergsdal et al. 2014). Pauliuk and colleagues (2013) embedding of life cycle assessment techniques into dynamic MFA to explore the maximal energy savings potential in the building sector. Further, demolition and renovation activities of the Norwegian dwelling stock are estimated in each year up to 2050 based on an extended segmented model (Sandberg et al. 2014a). After that, robustness of the Norwegian segmented dwelling stock model is validated by a sensitivity analysis (Sandberg et al. 2014b). Exemplified by the Norwegian dwelling stock, likewise, the well-established dynamic segmented model has served as an excellent tool to investigate the demolition activities, renovation activities, and energy demands in various cohorts of dwelling stock (Sartori et al. 2016; Sandberg et al. 2016b). This dynamic segmented model has been further applied to simulate the development of dwelling stocks in 11 European countries (Sandberg et al. 2016a). Additionally, a dynamic stock-driven material model has been widely exploited to simulate and forecast the evolution of building stocks in several other countries, such as the United States (Moura et al. 2015), Chile (Gallardo et al. 2014), Germany and Czech Republic (Vásquez et al. 2016), and Japan (Hatayama and Tahara 2016).

The present study falls within the stream of researches on the Chinese building stock. As the cornerstone sector of economy, the Chinese building stock is experiencing an unprecedented enlargement during the rapid urbanization process (Fernandez 2007). Figures derived from the China Statistical Yearbook indicate that the per capita floor area has multiplied in both the urban and rural residential sectors. During the period of 1978–2012, the per capita floor area of urban and rural residential buildings has increased from 6.7 to 32.9 square meters (m^2) and 8.1 to 37.1 m^2, respectively (NBSC 1983–2015). Accompanying simultaneous population growth and economic development, the total building stock has accumulated to 46.9 billion m^2 in 2012 (BERC 2013). The building material consumed in construction of the building stock accounts for a large part of China's energy consumptions and carbon dioxide emissions (Yang and Kohler 2008). It is estimated that more than 30% of the cement and steel produced in China in 2012 are consumed by the Chinese building stock (Wang et al. 2015). Because of the short lifetime of the Chinese building and the aging material accumulated in buildings (Cai et al. 2015), China will inevitably face huge environmental burdens from the waste stream of the building stock in the foreseen decades.

To achieve the long-term resource sustainability and emission reduction target in China's building sector, assessing the temporal evolution of the building stock is a prerequisite. A series of dynamic MFA models have been built to simulate the dynamic behavior of the Chinese building stock (Hu et al. 2010b; Yang and Kohler 2008), associated material flow (Hu et al. 2010a, 2010c, 2010d; Huang et al., 2013; Wang et al., 2015), and energy consumption and carbon emissions of construction material consumed by the newly added stock (Hong et al. 2016; Shi et al. 2012, 2016). The preceding studies, focusing on the dynamic material flow of Chinese building stock, usually conduct sensitivity analyses in their models by setting low, medium, and high scenarios. The outputs of sensitivity analyses are often single and deterministic values, thus neglecting the inherent uncertainties of input parameters in the dynamic MFA model. When applying the dynamic MFA model as a decision support tool for the resource management and emission control, consistent and transparent consideration of uncertainties in the dynamic MFA is required (Laner et al. 2015). Namely, the inherent variation of input parameters might have a strong influence on the model's output, which should be handled by systematic procedures. A probabilistic MFA model could help to improve the reliability and robustness of the dynamic MFA model (Müller et al. 2014). Accordingly, the dynamic MFA model concerning the building stock should define the probabilistic distribution of the model's input parameters, propagate the uncertainty through the model, and provide the confidence interval (CI) of the output, rather than providing a deterministic result (Booth et al. 2012).

To this end, the present article seeks to establish a probabilistic dynamic MFA model, which is based on the stock-driven model developed by Müller (2006), for a long-term development of the building stock. In consideration of data availability, China's urban housing stock is chosen as the empirical case for this model. The distinguishing features of the probabilistic dynamic MFA model for China's urban housing stock are as followings:

- In the probabilistic housing stock MFA model, the uncertainties in model inputs (i.e., the population, urbanization, housing floor area per capita, building lifetime, and material intensity) are handled by probabilistic methods.
- Using bootstrap and Monte Carlo simulation, the uncertainties in model outputs (i.e., the urban housing stock area, newly completed area, demolished area, material stock, and inflow and outflow) are evaluated by confidence ranges instead of single point values.
- Uncertainties in simulation results are analyzed by the Spearman's rank-correlation method that could identify

the most important contributor to uncertainties in model outputs.

A certain scenario is the key assumption in this study. The effect of prolonging the lifetime of the housing building (Huang et al. 2013; Shi et al. 2012) or reducing the material intensity (Hu et al. 2010c) has already been investigated by sensitivity analyses with low, medium, and high scenarios. Unlike sensitivity analysis, uncertainty analysis in the present study aims to figure out the range of the evolution pathway for China's urban housing stock, even under a certain scenario. Based on the probabilistic housing stock MFA model, the present study has provided an elaborate picture of the uncertainty in the development pathway of China's urban housing stock. Several policy implications and recommendations for decision makers and future dynamic MFA modelers are also discussed.

Methodology and Data Sources

Description of Dynamic Housing Stock Model

To extrapolate the future behavior of the in-use stock, three genres of dynamic modeling could be harnessed, that is, the retrospective and prospective bottom-up method, retrospective and prospective top-down method, and prospective top-down method. A detail review of the dynamic MFA methods can be found in a previous literature review (Müller et al. 2014). In the present article, the retrospective and prospective bottom-up method conceptualized by the review is to be used here (Müller et al. 2014). Thus, the dynamic housing stock model used in the present article is extended based on the extant stock-driven model derived from Müller's work (2006). For brevity, a general description of the stock-driven dynamic housing stock model is given herein.

In a stock-driven model, the inflow and outflow of the in-use stock are determined from the total stock size and lifetime (Pauliuk and Müller 2014). Inflows newly added into the housing stock are to satisfy the expanding housing floor area per capita and population growth or to maintain the existing housing stock. The in-use stock is analogous to a time buffer, meaning that the outflow is the delayed inflows with corresponding lifetime distributions (Kleijn et al. 2000). Mathematically, the relationship between the inflow and outflow can be expressed as a convolution. Combining the evolution of the in-use stock and outflow, the future inflow can be predicted. On the basis of the preceding principles, a dynamic model for China's urban housing stock is established as shown in equations (1), (2), and (3):

$$CA_t = SA_t - SA_{t-1} + DA_t \tag{1}$$

$$SA_t = P_t \cdot U_t \cdot a_t \tag{2}$$

t'年建造的房子在t年被拆除的概率

$$DA_t = \sum_{t'=t_0}^{t'=t-1} CA_{t'} \cdot (1 - S_{t-t'}) \tag{3}$$

where CA_t or $CA_{t'}$ refers to the newly completed floor area as inflows into the housing stock at time t or t'; SA_t or SA_{t-1} refers to the in-use housing stock (existing housing floor area) at time t or $t-1$; DA_t refers to the demolished floor area as outflows out of the housing stock at time t; P_t refers to the population at time t; U_t refers to the urbanization rate at time t; a_t refers to the urban housing floor area per capita at time t; and $S_{t-t'}$ refers to the probability that buildings survive for $t - t'$ years.

To investigate the inflow, outflow, and in-use material volume of China's urban housing stock, the material intensity of housing buildings in urban region should be included into the model. As expressed in equations (4), (5), and (6), the inflow, outflow, and in-use material volume related to urban housing stock equals to the newly, demolished, and in-use housing stock area multiplying by the material intensity:

$$M_{in,t} = CA_t \cdot MI_i \tag{4}$$

$$M_{out,i,t} = DA_t \cdot MI_i \tag{5}$$

$$M_{stock,i,t} = SA_t \cdot MI_i \tag{6}$$

where i refers to the material type; $M_{in,i,t}$ refers to the material inflow of construction material type i; $M_{out,i,t}$ refers to the material outflow of the construction material type i; and MI_i refers to the material intensity of the construction material type i.

Quantification of Uncertainties for Input Parameters

The dynamic housing stock model contains five fundamental components: per capita floor area (a_t); building lifetime (as represented by buildings survival rate; $S(t)$), population (P_t); urbanization rate (U_t); and material intensity (MI_i). When applying the Monte Carlo method to simulate the material inflow ($M_{in,t}$), outflow ($M_{out,i,t}$), and in-use of the housing stock ($M_{stock,i,t}$), the first step is to quantify uncertainties in the five fundamental components with probabilistic methods.

Uncertainties in Urban Housing Floor Area per Capita

The urban housing floor area per capita reflects the level of living condition in the urban region (Huang et al. 2013). A four-parameter logistic and Gompertz combined function (Liu et al. 2013), as shown in equation (7), is applied to define the saturation level and future growth of the housing floor area per capita:

$$a_t = \frac{a_{saturation}}{1 + \left(\frac{a_{saturation}}{a_0} - 1\right) \cdot e^{A(1-exp^{B(t-t_0)})}} \tag{7}$$

where a_t refers to the urban housing floor area per capita at time t; $a_{saturation}$ refers to the saturation level of the urban housing floor area; a_0 refers to the initial level of urban housing floor area at time t_0; and A and B are parameters that determine the growth patterns of the logistic curve. In line with the setting of logistic growth function in previous researches about China (e.g., Hu et al. 2010b, 2010c; Huang et al. 2013), a medium value of 50 m^2 is chosen as the saturation level for the urban

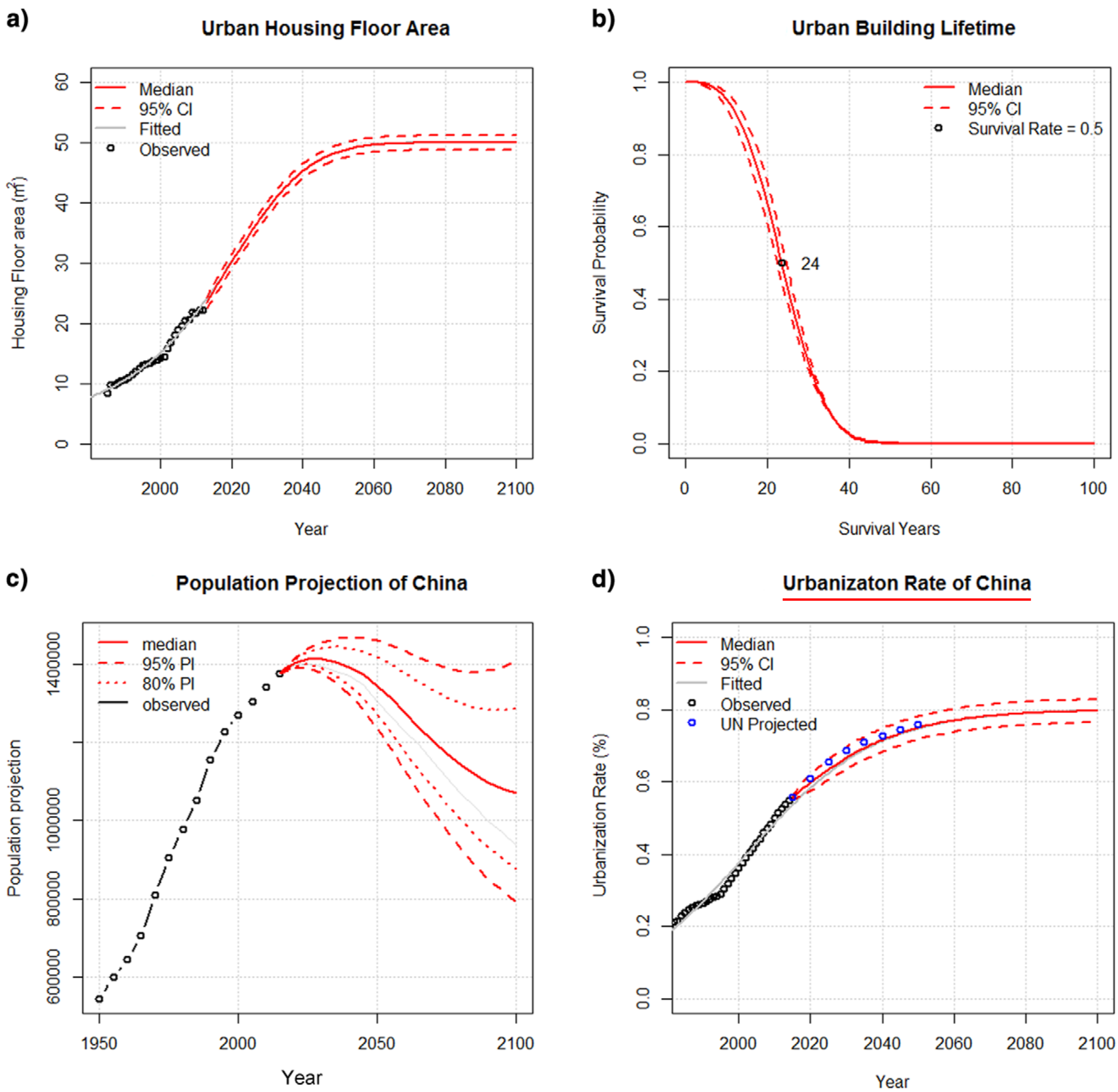

Figure 1 (a) Growth pattern of housing floor area per capita in China's urban region from 2015 to 2100. (b) Estimated lifetime (survival) function of China's urban housing buildings. (c) The projection for the Chinese population from 2015 to 2100. (d) The estimated growth pathway of Chinese urbanization rate from 2015 to 2100. CI = confidence interval; m^2 = square meters; PI = probability interval.

housing stock while a value of 2 m^2 is set as the initial level. Historical data of floor area in the urban region are quoted from the China Statistical Yearbook (NBSC 1983–2015). It is noted that the statistical survey of the urban housing floor area per capita in Chinese statistical data has excluded the floating population and collective registered residents (BERC 2013; CSSN 2014). Therefore, the urban housing floor area per capita is adjusted to be consistent with the permanent urban population.

The logistic function can well fit the growth pattern of the urban housing floor area. Nevertheless, there exist certain residuals in the empirical fitted regression model. To analyze the stochastic errors in the development of the urban housing floor area, the Autoregressive Integrated Moving Average (ARIMA) model is adopted here to distinguish the exogenous shock (Fishman et al. 2016). Details of the ARIMA method are presented in section S1 of the supporting information available on the Journal's website. As shown in figure 1a, the housing floor area of the urban region would reach the saturation level at around 2050.

Uncertainties in Building Lifetime

Although the design lifetime of normal buildings is 50 years in China (MCC 2005), the de facto average lifetime of Chinese buildings is as short as 30 years (Cai et al. 2015) and the life span of rural buildings is even shorter (Huang et al. 2013). Previous studies commonly applied crude assumption for the lifetime parameter (e.g., Hu et al. 2010b; Huang et al. 2013; Shi et al. 2012; Wang et al. 2015). The age distribution of the building stock can be described by the Weibull distribution (Erik Bradley and Kohler 2007). In light of this, Cai and colleagues (2015) have proposed a fitting method to obtain parameters of the age distribution function of the building stock. Based on Cai and colleagues' research, the lifetime function in the present study is defined as a two-parameter Weibull distribution function and the corresponding survival function is as follows (equation 8):

$$S(t) = exp\left(-\left(\frac{t}{\lambda}\right)^{k}\right) \tag{8}$$

where $S(t)$ refers to the probability that buildings survive for t years and λ and k refer to the scale parameter and shape parameter of the Weibull distribution, respectively.

The relation between the floor area completed and demolished annually is presented in equations (9) and (10):

$$D_{t',\ t} = \left[S(t - t' - 1) - S(t - t')\right] \cdot C_{t'} \tag{9}$$

$$D_t = \sum_{t'=t_0}^{t-1} D_{t',\ t} \tag{10}$$

where $D_{t',\ t}$ refers to the floor area completed in year t' and demolished in year t; $C_{t'}$ refers to the floor area completed in year t'; D_t refers to the total floor area demolished in year t; and $t_0 = 1982$ refers to the earliest floor area completed available in China. The floor area completed annually can be obtained from the annual official statistical publication (NBSC 1983–2015). The floor area demolished annually is calculated using the estimation approach proposed by Cai and colleagues (2015). Because D_t and $C_{t'}$ are available, the two parameters (scale and shape) of Weibull distribution can be estimated. Details can be found in section S2 in the supporting information on the Web.

There also exist errors within the estimated parameters derived by fitting methods. To acquire random values for the scale and shape of the lifetime function, the bootstrap method is adopted here to prepare the input of Monte Carlo simulation. As presented in figure 1b, the average life span of residential buildings in the urban region is 24 years and median values of the scale and shape parameter for survival function are 27 and 3.2, respectively. The estimated average lifetime is consistent with the result in Cai and colleagues' work (2015).

Uncertainties in Population

The population is one of the underlying driving factors for the housing stock (Hu et al. 2010b). To introduce uncertainty in the population, the present article has adopted a probabilistic population projection using Bayesian hierarchical models estimated by the Markov chain Monte Carlo (MCMC) (Raftery et al. 2012).

The population projection model is proposed by Raftery and colleagues (2012) and is composed of two submodels: a total fertility rate projection model (Alkema et al. 2011) and a life expectancy projection model (Raftery et al. 2013). A double-logistic function with previous distributed parameters is presumed in the population projection model, after which world-level observed population data and a MCMC algorithm are used to compute the posterior distributions of parameters. Data of historical total fertility rate and life expectancy are obtained from the United Nations (UN) Population Division (UNDP 2015).

The population projection is computed by three R packages, bayesPop (Ševčíková and Raftery 2012.), bayesTFR (Ševčíková et al. 2011), and bayesLife (Ševčíková and Raftery 2011.). The detail description of population projection method is presented in section S3 of the supporting information on the Web. The simulation result for the population projection is displayed in figure 1c. Results of the total fertility rate and life expectancy are displayed in section S3 the supporting information on the Web. Samples from the posterior distributions of parameters will be served as inputs of the Monte Carlo simulation in the dynamic housing stock model.

Uncertainties in Urbanization

The urbanization rate is also a vital driving factor for the housing stock model. The S-curve logistic formula, derived from Liu and colleagues (2003), is applied to fit the future urbanization rate of China (registered population). The saturation level of the urbanization rate has been adjusted to keep consistent with the projection from the UN Population Division. The S-curve formula is expressed as equation (11):

$$U_t = \frac{0.8}{1 + \alpha \cdot e^{-\beta(t-t_0)}} \tag{11}$$

where U_t refers to the urbanization rate at time t; α and β refers to the shape parameters that control the growth patterns; and t_0 refers to the initial date, which is set as 1986. Data of population urbanization rate are obtained from the China Population & Employment Statistics Yearbook (NBSPSD 1988–2014).

As the same as the housing floor area per capita, the ARIMA model is also used here to include the stochastic errors in the development of the urbanization rate. Details of the ARIMA model are presented in section S4 of the supporting information on the Web. As presented in figure 1d, the growth pathway of the urbanization rate for the registered population is in parallel with the projection by the UN Population Division (UNDP 2014), which has fallen into the 95% CIs of estimation results in the present paper.

Uncertainties in Material Intensity

The probability distribution functions for various building materials are obtained by the maximum likelihood estimation and bootstrap simulation (Frey and Bammi 2002), other than providing a deterministic value of the average material intensity in previous researches (e.g., Hong et al. 2016; Hu et al. 2010c, 2010d; Huang et al. 2013; Shi et al. 2012, 2016). Nine species of main building materials (i.e., cement, steel, wood, brick, gravel,

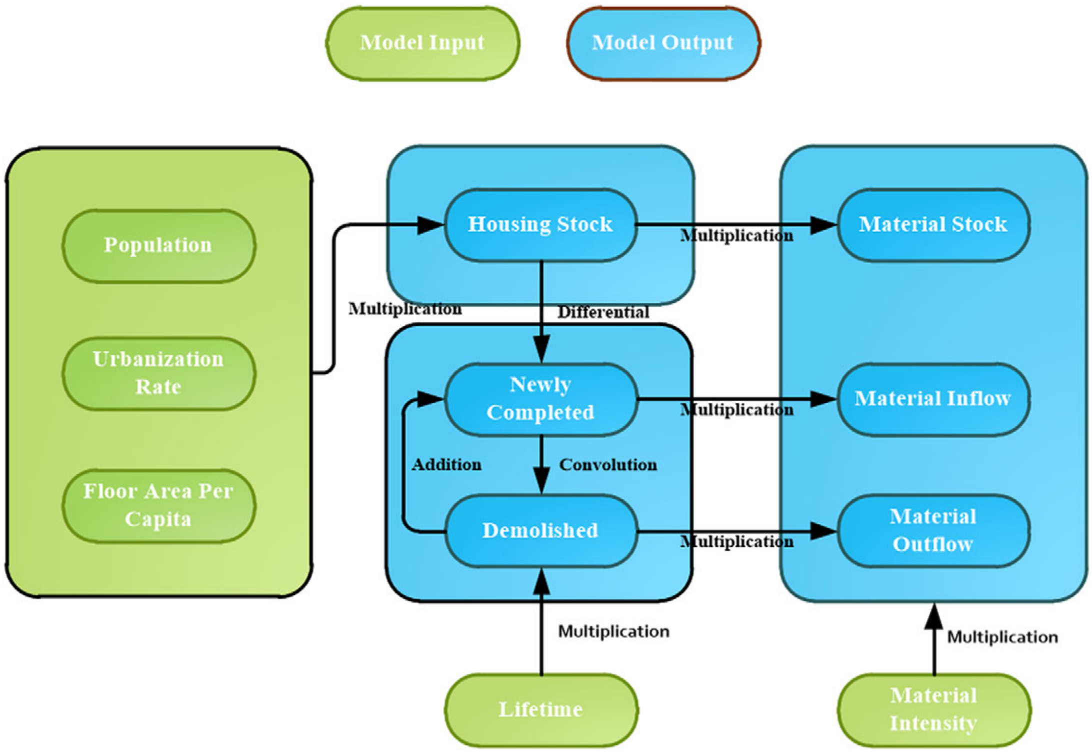

Figure 2 Diagram of propagation uncertainties in the probabilistic dynamic housing stock model.

sand, asphalt, lime, and glass) are taken into consideration to quantify the material metabolism of the Chinese housing stock.

The assumption of the symmetric normal distribution is not always compatible with empirical data (Laner et al. 2014). The intensities of building material are usually non-negative variables and are known to be positively skewed. Therefore, a skewed distribution, such as lognormal, Weibull, or Gamma, might better fit observed data (Cao et al. 2016). One hundred forty-six urban residential building project samples, including various kinds of building structure, are collected from the Construction Project Investment Estimation Handbook (Yu and Li 1999). The building project samples might be somewhat outdated, and up-to-date samples for the building material intensity are still lacking. Nevertheless, the variation in the building material intensity still could be reflected in this sample.

It takes three steps to produce the input of the material intensity for the Monte Carlo simulation. The first step is to select the best-fitting PDF for the material intensity. According to three classical statistics (i.e., Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling statistics) and two fitting evaluation criteria (Aikake's Information Criteria and Bayesian Information Criteria), the best-fitting PDF for the material intensity of each type is selected (Delignette-Mullerand Dutang 2014). The second step is to calculate parameters of PDF for each building material type with the bootstrap simulation. The last step is to generate random samples for the Monte Carlo simulation from the estimated distribution functions.

The detailed procedures and results could be found in sections S5, S6, and S7 of the supporting information on the Web. The goodness-of-fit statistics and criteria for various types of materials are listed in table S10 (see section S6 of the supporting information on the Web). The median of parameters for PDF simulated by the bootstrap method in the second step and 95% CIs of the random samples for each building material are listed in table S11 (see section S7 of the supporting information on the Web). It is found that seven of ten building materials have asymmetric distributions. The histograms of various building material types generated in the last step could be found in figure S2 (see the section S5 of the supporting information on the Web).

Uncertainty Propagation and Uncertainty Importance Analysis

Uncertainty information provided in the section *Quantification of Uncertainties for Input Parameters* forms the basis to propagate uncertainties in the five components to the outputs. A brief description of the uncertainty propagation is displayed in figure 2. Propagation of uncertainties from model inputs to model outputs is achieved by the Monte Carlo simulation and bootstrap sampling. By 5,000 repetitions of computation, the 95% CIs of housing stock dynamics and related material flows are provided. All probabilistic simulations, including the fitting, bootstrap, ARIMA, Monte Carlo, and MCMC, are implemented on the R program platform.

Because the uncertainty importance analysis gives better knowledge of the model outputs, the uncertainty importance of five components for the simulation output is evaluated by

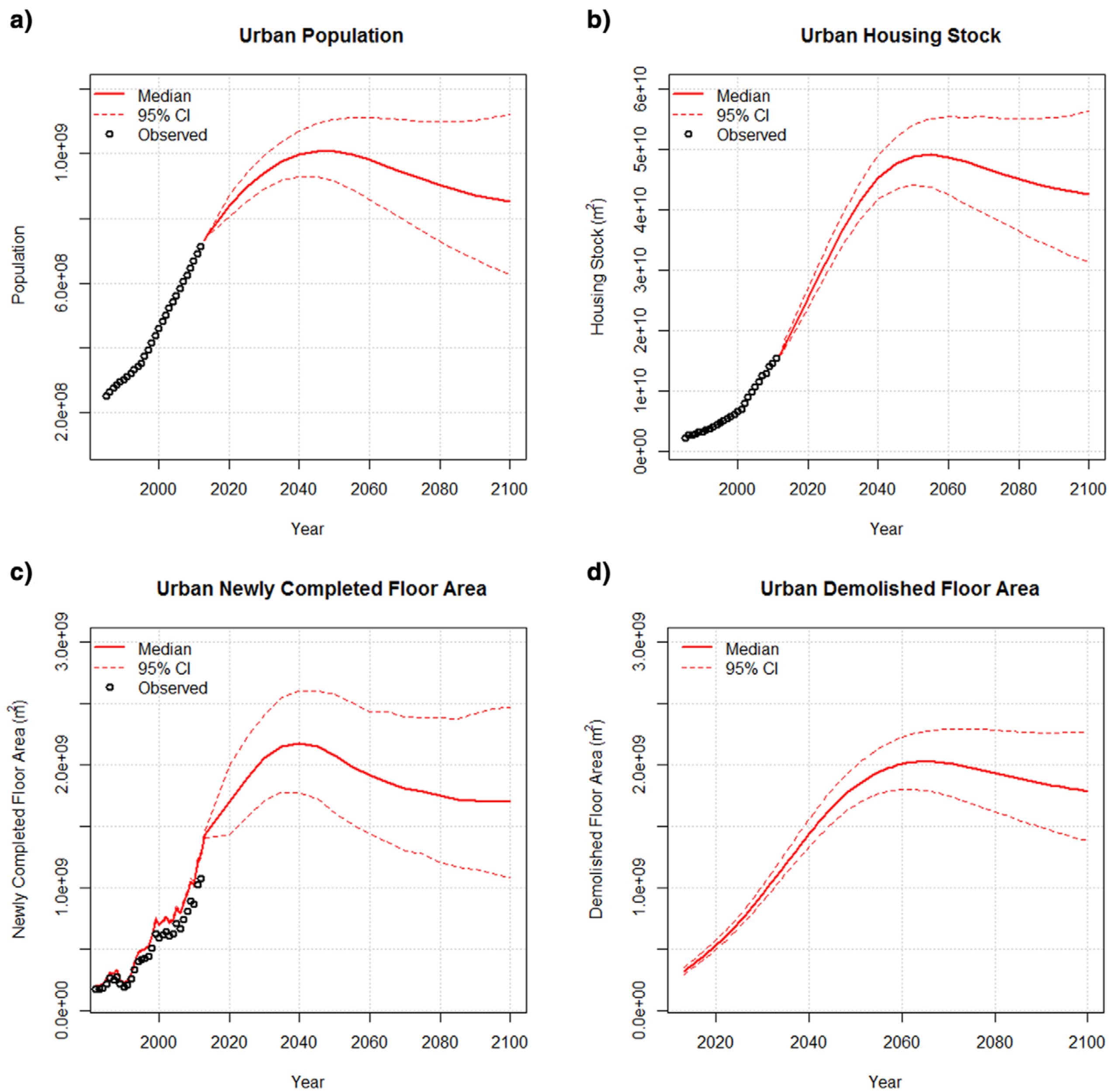

Figure 3 Evolution pathways of (a) urban population; (b) urban housing stock; (c) urban newly completed floor area; and (d) urban demolished floor area from 1985 to 2100 (median and 95% confidence intervals are provided). CI = confidence interval; m^2 = square meters.

the Spearman's rank-correlation coefficient. The uncertainty importance analysis can provide the information that which input parameters have the most importance for the final result (Sonnemann et al. 2003). The Spearman's rank-correlation coefficient is a nonparametric technique for assessing the degree of linear correlation between two variables (Gautheir 2001). The Spearman's rank-correlation coefficient of two variables is calculated as the following formula (equation 12):

$$rho = \frac{1 - 6\sum_{1}^{n} d_i^2}{n^3 - n} \tag{12}$$

where rho refers to the Spearman's rank correlation coefficient of two variables; d_i is the difference between ranks for each variable; and n is the number of variable pairs. In addition, the contribution of the five components to the variance of model outputs is expressed as the normalized squares of Spearman's rank-correlation coefficients (equation 13):

$$C_i = \frac{r_i^2}{\sum {r_i}^2} \tag{13}$$

where C_i refers to the relative contribution of an input parameter i to the variance of output result and r_i is the Spearman's

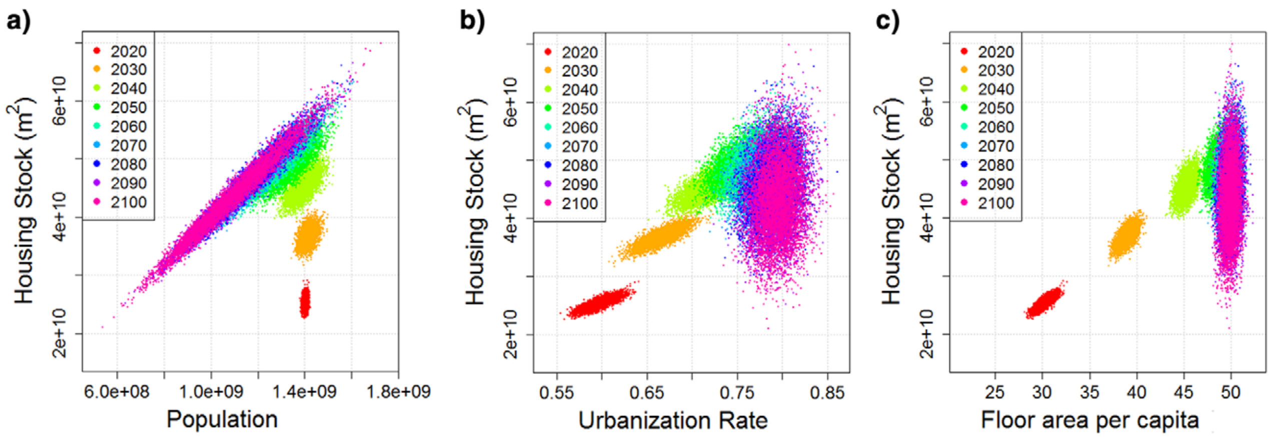

Figure 4 Scatter plots of (a) the total population and the urban housing stock, (b) the urbanization rate and the urban housing stock, and (c) the floor area per capita and the urban housing stock (discrete simulation results selected from 2020 to 2100). m^2 = square meters.

rank-correlation coefficient between the input parameter *i* and output result.

According to figure 2, the housing stock at every year is only related to the contemporaneous population, urbanization rate, and per capita floor area. The material stock is only related to the contemporaneous population, urbanization rate, per capita floor area, and material intensity as well. For the newly completed area, demolished area and corresponding material flows, the time-delay effects have to be considered. Uncertainties in the newly completed area and the demolished area at one year might be impacted by the preceding evolution of the population, urbanization rate, and per capita floor area. The detailed explanation of time-delay effect is demonstrated in section S11 of the supporting information on the Web. According to the propagation of errors, uncertainties in the population, urbanization rate, and floor area per capita in every preceding year would be propagated to the newly completed floor area and demolished floor area in the current year. In this regard, the newly completed floor area, demolished floor area, and corresponding material flows in 2100 are to be selected as examples to illustrate the time-delay effect given that the model outputs in this specific year has covered the whole historical model inputs.

Results and Discussion

Evolution of the Urban Housing Stock

The evolution patterns of the urban population and urban housing stock are displayed in figure 3a and 3b. The urbanization rate and the urban population will, respectively, reach 75% (see figure 1d) and 1.01 billion (see figure 3a) around 2050. The median value of the pathway demonstrates that the urban housing stock will peak at 49 billion m^2 around 2050 (see figure 3b). The median value of the urban housing stock in the present study is close to the results in previous studies, for example, 48 billion m^2 (Hu et al. 2010b) and 44 billion m^2 (Huang et al. 2013). A decrease in population might not necessarily give rise to the decrease in the housing stock (Hashimoto et al. 2007). The trend of urban housing stock is codetermined by the total population, urbanization rate, and per capita floor area. After 2050, accompanied by the decline in the total population and almost saturation in the floor area per capita and urbanization rate, the urban housing stock starts to present a decreasing tendency.

Note that CIs of the urban housing stock are getting wider during the evolution process. The relative uncertainty in the urban housing stock is [–6.4%, +6.8%] in 2020 and [–27%, +32%] in 2100. This tendency seems to be consistent with the evolution tendency of the urban population. The relative uncertainty of the urban population is [–4.1%, +4.0%] in 2020 and [–26%, +31%] in 2100. According to figure 4, the variance in the urban housing stock is spreading up and uncertainies in the urban housing stock are tending to be highly related to uncertainties in the total population during 2020–2100 (separate figures are demonstrated in section S12 of the supporting information on the Web). This indicates that the variance of the total population is increasingly leading to a variation in the urban housing stock. The correlation between uncertainties in the urban housing stock and uncertainties in the urbanization rate is decreasing during 2020–2100. The similar tendency could be found in the correlation between uncertainties in the urban housing stock and uncertainties in the floor area per capita. This would be explained by the reduction of uncertainties in the urbanization rate and the floor area per capita given that their variances are shrinking.

According to equation (2), the total population is not the only determinant to the uncertainty in the urban housing stock. The uncertainty in urban housing stock is codetermined by three inputs: total population, urbanization rate, and urban housing floor area per capita. The contributions of the three inputs are listed in figure 5a. Although the level of the population is decreasing, the variance in the population is increasing. The combined contribution of the urbanization rate and floor area per capita is higher than that of the total population before 2040; since 2050, the contribution of the total population has exceeded 50%. As can be seen, the effect of the urbanization

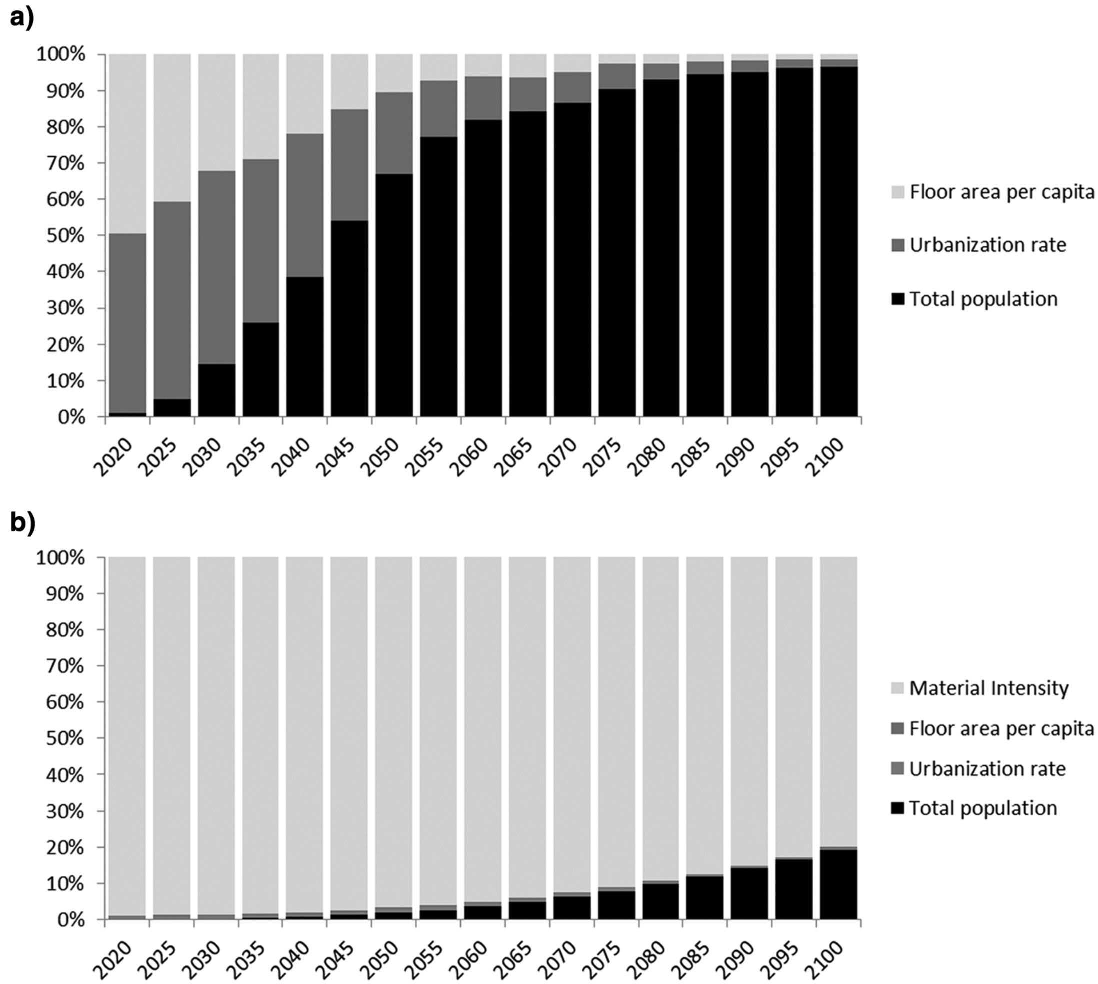

Figure 5 (a) Contribution of the total population, urbanization rate, and floor area per capita to the variance in the urban housing stock. (b) Contribution of the total population, urbanization rate, floor area per capita, and material intensity to the variance in the material stock.

rate and the urban housing floor area per capita on the uncertainty of urban housing stock is less critical in the long term.

Newly Completed and Demolished Floor Area

The evolution patterns of the newly completed floor area (1985–2100) and demolished floor area (2013–2100) are illustrated in figure 3c and 3d. The annual newly completed floor area of the urban housing stock shows an overall upward trend and the median value of that is expected to peak at 2.2 billion m^2 in 2040, subsequently, declines to approximately 1.7 billion m^2 for around 50 to 60 years. On the other hand, the annual demolished floor area also presents a growing tendency and will mount to 2.0 billion m^2 in 2065. The annual demolished floor area will peak later than the annual newly completed floor area given that the newly added housing stock accommodated for the urban migration during 2040–2065 has not reached the average lifetime. Historical statistical (observed) data of the newly completed floor area have validated the model, although the modeling value is slightly higher than the statistical data. This might be an inconsistency in the official statistics in which a small fraction of building activity in the small town is not considered (Yang 2006).

The relative uncertainty in the newly completed floor area is [–16%, +17%] in 2020 and [–36%, +45%] in 2100, whereas the relative uncertainty in the demolished floor area is [–6.5%, +7.7%] in 2020 and [–23%, +27%] in 2100. To examine the time-delay effect of model inputs on the newly completed and demolished floor area, the uncertainty importance analysis is carried out for these two model outputs in 2100. As presented in figure 6, the time-delay effect of uncertainties in the total population is significant, which, respectively, contributes a total of 97.68% and 98.29% to the uncertainties in year 2100's newly completed and demolished floor area. It is should be noted that the contribution of the total population from 2013 to 2100 is climbing up, except that the contribution of the total population in 2095 is relatively lower than the previous. This could be attributed to the fact that a large proportion of the newly completed floor area in 2095 that arose by the increase of the population in 2095 has not reached their lifetime. The contribution of other four inputs is negligible given that the

Relative variation (RV) and contribution (CON) of each input to 2100's newly completed floor area

	RV	CON		RV	CON		RV	CON		RV	CON
P_{2013}	0.00%	0.00%	U_{2013}	0.00%	0.00%	a_{2013}	7.40%	0.05%	λ	7.26%	0.10%
P_{2014}	0.00%	0.00%	U_{2014}	0.00%	0.00%	a_{2014}	8.50%	0.07%	k	22.51%	0.00%
P_{2015}	0.00%	0.00%	U_{2015}	1.99%	0.05%	a_{2015}	8.94%	0.06%			
P_{2020}	1.68%	1.45%	U_{2020}	7.87%	0.07%	a_{2020}	7.95%	0.01%			
P_{2025}	3.48%	2.55%	U_{2025}	9.12%	0.03%	a_{2025}	7.00%	0.01%			
P_{2030}	5.74%	3.33%	U_{2030}	9.07%	0.00%	a_{2030}	6.00%	0.00%			
P_{2035}	8.01%	3.77%	U_{2035}	9.13%	0.00%	a_{2035}	5.65%	0.00%			
P_{2040}	10.54%	4.13%	U_{2040}	9.00%	0.00%	a_{2040}	5.25%	0.00%			
P_{2045}	13.39%	4.57%	U_{2045}	8.91%	0.00%	a_{2045}	5.04%	0.00%			
P_{2050}	16.81%	5.09%	U_{2050}	8.51%	0.00%	a_{2050}	4.91%	0.00%			
P_{2055}	20.42%	5.58%	U_{2055}	8.35%	0.00%	a_{2055}	4.88%	0.01%			
P_{2060}	24.23%	6.02%	U_{2060}	8.25%	0.00%	a_{2060}	4.70%	0.01%			
P_{2065}	27.81%	6.45%	U_{2065}	8.23%	0.00%	a_{2065}	4.84%	0.00%			
P_{2070}	31.52%	6.88%	U_{2070}	8.20%	0.00%	a_{2070}	4.81%	0.01%			
P_{2075}	35.48%	7.29%	U_{2075}	8.05%	0.00%	a_{2075}	4.82%	0.00%			
P_{2080}	39.80%	7.65%	U_{2080}	8.09%	0.00%	a_{2080}	4.85%	0.01%			
P_{2085}	44.00%	7.94%	U_{2085}	8.24%	0.00%	a_{2085}	4.86%	0.01%			
P_{2090}	48.68%	8.16%	U_{2090}	8.06%	0.01%	a_{2090}	4.84%	0.13%			
P_{2095}	52.96%	8.33%	U_{2095}	8.01%	0.15%	a_{2095}	4.90%	0.01%			
P_{2100}	57.65%	8.48%	U_{2100}	7.94%	0.05%	a_{2100}	4.77%	1.44%			
Σ		97.68%	Σ		0.37%	Σ		1.84%			

Relative variation (RV) and contribution (CON) of each input to 2100's demolished floor area

	RV	CON		RV	CON		RV	CON		RV	CON
P_{2013}	0.00%	0.00%	U_{2013}	0.00%	0.00%	a_{2013}	7.40%	0.05%	λ	7.26%	0.18%
P_{2014}	0.00%	0.00%	U_{2014}	0.00%	0.00%	a_{2014}	8.50%	0.08%	k	22.51%	0.01%
P_{2015}	0.00%	0.00%	U_{2015}	1.99%	0.05%	a_{2015}	8.94%	0.07%			
P_{2020}	1.68%	1.79%	U_{2020}	7.87%	0.06%	a_{2020}	7.95%	0.00%			
P_{2025}	3.48%	3.12%	U_{2025}	9.12%	0.02%	a_{2025}	7.00%	0.01%			
P_{2030}	5.74%	4.09%	U_{2030}	9.07%	0.00%	a_{2030}	6.00%	0.00%			
P_{2035}	8.01%	4.62%	U_{2035}	9.13%	0.00%	a_{2035}	5.65%	0.00%			
P_{2040}	10.54%	5.04%	U_{2040}	9.00%	0.00%	a_{2040}	5.25%	0.00%			
P_{2045}	13.39%	5.50%	U_{2045}	8.91%	0.00%	a_{2045}	5.04%	0.00%			
P_{2050}	16.81%	6.03%	U_{2050}	8.51%	0.00%	a_{2050}	4.91%	0.00%			
P_{2055}	20.42%	6.49%	U_{2055}	8.35%	0.00%	a_{2055}	4.88%	0.00%			
P_{2060}	24.23%	6.87%	U_{2060}	8.25%	0.00%	a_{2060}	4.70%	0.00%			
P_{2065}	27.81%	7.21%	U_{2065}	8.23%	0.00%	a_{2065}	4.84%	0.01%			
P_{2070}	31.52%	7.52%	U_{2070}	8.20%	0.02%	a_{2070}	4.81%	0.04%			
P_{2075}	35.48%	7.78%	U_{2075}	8.05%	0.06%	a_{2075}	4.82%	0.06%			
P_{2080}	39.80%	7.98%	U_{2080}	8.09%	0.12%	a_{2080}	4.85%	0.12%			
P_{2085}	44.00%	8.09%	U_{2085}	8.24%	0.22%	a_{2085}	4.86%	0.08%			
P_{2090}	48.68%	8.10%	U_{2090}	8.06%	0.23%	a_{2090}	4.84%	0.04%			
P_{2095}	52.96%	8.06%	U_{2095}	8.01%	0.17%	a_{2095}	4.90%	0.01%			
Σ		98.29%	Σ		0.94%	Σ		0.58%			

Figure 6 Relative variation (RV) and contribution (CON) of each input to 2100s newly completed floor area and 2100s demolished floor area. *Note*: RV = (quantile 97.5%-quantile 2.5%)/median.

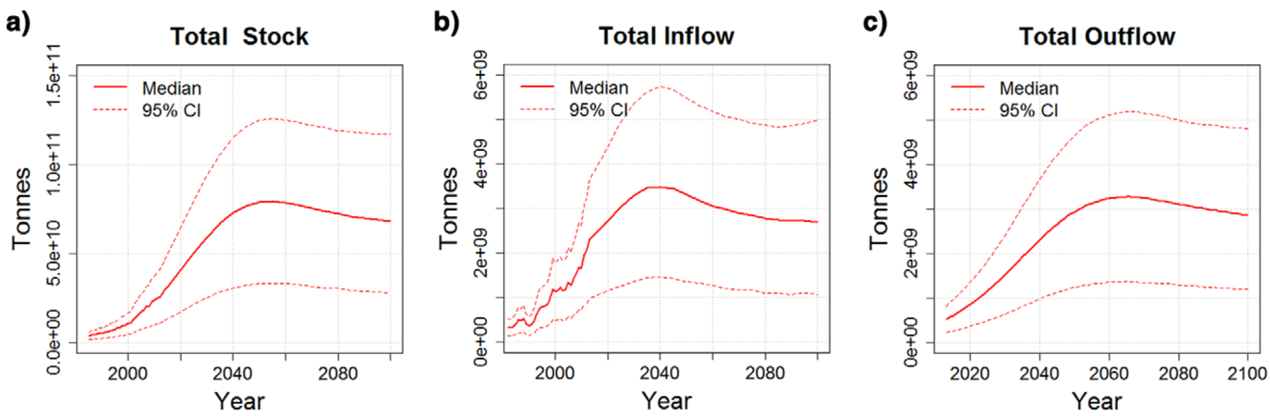

Figure 7 Evolution pathways of the (a) total material stock, (b) inflow, and (c) outflow of China's urban housing stock. CI = confidence interval.

magnitudes of these model inputs are relative smaller than the total population.

Material Stock, Inflow, and Outflow

As shown in figure 7, median values of the material stock, annual inflow, and annual outflow of the urban housing stock will peak at 79, 3.5, and 3.3 billion tonnes, respectively. The tendency of the material stock, annual inflow, and annual outflow are found to be similar to the floor area of urban housing stock, newly completed and demolished; however, the 95% CIs of the former three have wider spreads. The relative 95% CIs of material stock are [–58%, +58%] in 2020 and [–59%, +72%] in 2100, whereas the relative 95% CIs of the material inflow are [–57%, +61%] in 2020 and [–61%, +86%] in 2100 and that of the material outflow are [–57.96%, +58.74%] in 2020 and [–58.18%, +68.14%] in 2100. The material flows of various material types are displayed in section S10 of the supporting information on the Web.

For material metabolism, the variance in the material intensity is included in the uncertainty importance analysis, besides the total population, urbanization rate, floor area per capita, and scale and shape of building survival function. As shown in figure 5b, the material intensity emerges as the most influential contributor (more than 80% almost at every time point) to the uncertainty in the material stock during 2020–2100. As the increase of the variance in the total population, the contribution of the total population is strengthened.

The contribution of each model inputs to the material inflow and outflow in 2100 is displayed in figure 8. The effect of uncertainties in the total population is less notable for uncertainties in material flows compared to the effect of the total population to floor area dynamics of the urban housing stock. The time-delay effect of uncertainties in the total population contributes a total of 79% and 66% to the uncertainties in year 2100's material inflow and material outflow. The relative variation of the material intensity is much lager than the other model inputs, which has diluted the relative importance of uncertainties in the total population.

Discussion and Implication

It is worthy of note that conspicuous uncertainty exists in the inputs of the dynamic housing stock model and these uncertainties have been propagated into the future evolution of China's urban housing stock. Neglecting uncertainties in input parameters would lead to an over- or underestimation on material flows of China's urban housing stock. The pursuit of a systematic procedure for handling the uncertainty in the dynamic housing stock MFA model is to avoid an incomplete or partial analysis that might lead to misleading policy.

For the housing stock area's evolution, the total population will be the most influential parameter for a more precise prediction on the floor areas of the housing stock given that its relative variations are expanding. Previous studies have neglected the significant impact of population dynamics on housing stock's dynamics. Variations in population might exert significant impacts on the housing stock and the related construction and demolished floor area. For the housing stock material's evolution, the material intensity is the leading contributor to variances in material dynamics when the material intensity is incorporated into the probabilistic housing stock MFA model. This is because the variance in the material intensity has been propagated into the outputs of material dynamics and the effect of uncertainties in other model inputs has been diluted. Further, the uncertainty importance analysis has uncovered the time-delay effect of uncertainties inherent model inputs of dynamic housing stock model.

The implications of these observations are that uncertainty in input variables has to be taken seriously, both in a modeling and a long-term policy perspective (Sandberg et al. 2014b). This highlights the need to better understand the relationship between inputs and outputs of a housing stock MFA model. The range of results from China's urban housing stock MFA model suggests that no single point estimate should be taken as the representative for the urban housing stock's material metabolism. Taking a deterministic value to assess future resource and environmental impacts of the urban housing stock might lead to misleading policies. A failure of policy, which aims to reduce

Relative variation (RV) and contribution (CON) of each input to 2100's material inflow											
	RV	CON		RV	CON		RV	CON		RV	CON
P_{2013}	0.00%	0.00%	U_{2013}	0.00%	0.00%	a_{2013}	7.40%	0.02%	λ	7.26%	0.06%
P_{2014}	0.00%	0.00%	U_{2014}	0.00%	0.00%	a_{2014}	8.50%	0.05%	k	22.51%	0.02%
P_{2015}	0.00%	0.00%	U_{2015}	1.99%	0.02%	a_{2015}	8.94%	0.04%	MI	115.80%	18.76%
P_{2020}	1.68%	1.22%	U_{2020}	7.87%	0.06%	a_{2020}	7.95%	0.06%			
P_{2025}	3.48%	2.10%	U_{2025}	9.12%	0.05%	a_{2025}	7.00%	0.01%			
P_{2030}	5.74%	2.72%	U_{2030}	9.07%	0.00%	a_{2030}	6.00%	0.00%			
P_{2035}	8.01%	3.13%	U_{2035}	9.13%	0.00%	a_{2035}	5.65%	0.00%			
P_{2040}	10.54%	3.40%	U_{2040}	9.00%	0.00%	a_{2040}	5.25%	0.00%			
P_{2045}	13.39%	3.76%	U_{2045}	8.91%	0.01%	a_{2045}	5.04%	0.00%			
P_{2050}	16.81%	4.15%	U_{2050}	8.51%	0.01%	a_{2050}	4.91%	0.01%			
P_{2055}	20.42%	4.51%	U_{2055}	8.35%	0.00%	a_{2055}	4.88%	0.00%			
P_{2060}	24.23%	4.86%	U_{2060}	8.25%	0.01%	a_{2060}	4.70%	0.02%			
P_{2065}	27.81%	5.20%	U_{2065}	8.23%	0.00%	a_{2065}	4.84%	0.01%			
P_{2070}	31.52%	5.53%	U_{2070}	8.20%	0.01%	a_{2070}	4.81%	0.00%			
P_{2075}	35.48%	5.85%	U_{2075}	8.05%	0.01%	a_{2075}	4.82%	0.00%			
P_{2080}	39.80%	6.12%	U_{2080}	8.09%	0.00%	a_{2080}	4.85%	0.01%			
P_{2085}	44.00%	6.35%	U_{2085}	8.24%	0.00%	a_{2085}	4.86%	0.01%			
P_{2090}	48.68%	6.53%	U_{2090}	8.06%	0.02%	a_{2090}	4.84%	0.09%			
P_{2095}	52.96%	6.67%	U_{2095}	8.01%	0.15%	a_{2095}	4.90%	0.02%			
P_{2100}	57.65%	6.81%	U_{2100}	7.94%	0.04%	a_{2100}	4.77%	1.50%			
Σ		78.91%	Σ		0.39%	Σ		1.88%			

Relative variation (RV) and contribution (CON) of each input to 2100's material outflow											
	RV	CON		RV	CON		RV	CON		RV	CON
P_{2013}	0.00%	0.00%	U_{2013}	0.00%	0.00%	a_{2013}	7.40%	0.00%	λ	7.26%	0.09%
P_{2014}	0.00%	0.00%	U_{2014}	0.00%	0.00%	a_{2014}	8.50%	0.05%	k	22.51%	0.03%
P_{2015}	0.00%	0.00%	U_{2015}	1.99%	0.00%	a_{2015}	8.94%	0.05%	MI	115.80%	32.92%
P_{2020}	1.68%	1.27%	U_{2020}	7.87%	0.06%	a_{2020}	7.95%	0.08%			
P_{2025}	3.48%	2.14%	U_{2025}	9.12%	0.04%	a_{2025}	7.00%	0.01%			
P_{2030}	5.74%	2.79%	U_{2030}	9.07%	0.00%	a_{2030}	6.00%	0.00%			
P_{2035}	8.01%	3.23%	U_{2035}	9.13%	0.00%	a_{2035}	5.65%	0.00%			
P_{2040}	10.54%	3.48%	U_{2040}	9.00%	0.00%	a_{2040}	5.25%	0.00%			
P_{2045}	13.39%	3.79%	U_{2045}	8.91%	0.00%	a_{2045}	5.04%	0.01%			
P_{2050}	16.81%	4.09%	U_{2050}	8.51%	0.02%	a_{2050}	4.91%	0.02%			
P_{2055}	20.42%	4.35%	U_{2055}	8.35%	0.01%	a_{2055}	4.88%	0.01%			
P_{2060}	24.23%	4.59%	U_{2060}	8.25%	0.02%	a_{2060}	4.70%	0.02%			
P_{2065}	27.81%	4.80%	U_{2065}	8.23%	0.00%	a_{2065}	4.84%	0.02%			
P_{2070}	31.52%	4.98%	U_{2070}	8.20%	0.04%	a_{2070}	4.81%	0.02%			
P_{2075}	35.48%	5.14%	U_{2075}	8.05%	0.06%	a_{2075}	4.82%	0.01%			
P_{2080}	39.80%	5.24%	U_{2080}	8.09%	0.09%	a_{2080}	4.85%	0.09%			
P_{2085}	44.00%	5.30%	U_{2085}	8.24%	0.14%	a_{2085}	4.86%	0.04%			
P_{2090}	48.68%	5.31%	U_{2090}	8.06%	0.12%	a_{2090}	4.84%	0.04%			
P_{2095}	52.96%	5.30%	U_{2095}	8.01%	0.08%	a_{2095}	4.90%	0.00%			
Σ		65.81%	Σ		0.69%	Σ		0.46%			

Figure 8 Relative variation (RV) and contribution (CON) of each input to 2100s material inflow and 2100s material outflow. *Note*: RV = (quantile97.5%-quantile2.5%)/median.

the environmental impact of the urban housing stock through lifetime prolonging or material recycling, certainly occurs if the two important uncertainty contributors (i.e., the total population and the material intensity) are tending to lie above the median pathway. The Chinese government has started to loosen its control on population growth since 2016. Once the total population is tending to lie above the median pathway, policy makers in the housing sector should also consider raising the material efficiency (i.e., reducing the material intensity) of the newly built floor area as an essential policy to mitigate the material flows of the urban building stock and to lower the risk of policy failures.

Conclusions

Formulating rational policy and regulatory strategy for the housing stock depends on better understanding uncertainties in the future stock evolution and attendant environmental impacts. In this article, a probabilistic housing stock MFA model is established to estimate the future material dynamics of China's urban housing stock. This model has integrated the available data of China's urban housing stock and several probabilistic methods, which goes further than extant dynamic models that only provide deterministic outputs. An uncertainty analysis is carried out to demonstrate and elaborate the evolution pathway and confidence range of the housing stock, newly completed area, demolished area, material stock, and inflow and outflow from 1985 to 2100.

Results from the probabilistic housing stock MFA model demonstrate that the estimated median value of the material stock, annual inflow, and annual outflow would peak at 79, 3.5, and 3.3 billion tonnes, respectively. The relative uncertainties of material dynamics are above 50%. The uncertainty importance analysis reveals that the main contributors to these uncertainties are the material intensity and total population. Results from the probabilistic housing stock MFA model in the present study underline the complexity in China's housing stock. Consequently, cautions must be exercised by the policy makers in China's housing sector when formulating related policies for the housing stock.

There still remains the need to assess uncertainties in material dynamics in other building sectors. Only the urban housing stock in China is taken as an empirical example of the probabilistic MFA model. Similar analysis for the rural housing stock or the nonresidential building stock could be carried out if related data are available. In light of substantial uncertainties in the dynamic housing stock model, designing a policy option mechanism that could ensure the probability of success of the policy is also needed in the future research.

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Supporting Information

Supporting information is linked to this article on the *JIE* website:

Supporting Information S1: This supporting information contains detailed information on models and data sources. Results for parameters of material intensity's PDF are presented in section S7. Results for material flows of various material types are presented in section S10. Spearman's rank-correlation coefficients between the total population and the urban housing stock are presented in section S12.