

High spatial resolution mapping of steel resources accumulated above ground in mainland China: Past trends and future prospects

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ABSTRACT

High-resolution mapping of steel resources accumulated above ground (referred to as steel stocks) is critical for exploring urban mining and circular economy opportunities. Prior studies have attempted to approximate steel stocks using nighttime light (NTL). Although proven to be a fast estimation technique, the accuracy of the NTL-based approach may be subject to several limitations, and it has not been used for projecting future steel stocks. To fill these gaps, we developed an aggregative downscaling model that fuses multiple large-scale spatial datasets, including gridded population, gross domestic product (GDP), and built-up area. We demonstrated the utility of this model by using it to map steel stocks in mainland China at 1×1 km resolution. Our results found the steel stocks increased from 12,873 t/km² to 33,027 t/km² during 1995–2015, and four steel stocks clusters (i.e., Beijing-Tianjin-Hebei agglomeration, Yangtze River Delta, Guangdong-Hong Kong-Macao Greater Bay Area, and Chengdu-Chongqing metropolitan) possessed over 40% of the national total in 2015, revealing an unbalanced distribution of steel stocks across China. Moving forward, with the assumed population growth, GDP growth, and built-up area expansion, steel accumulation is expected to climb up to 64,636 t/km² and concentrate in larger cities in 2030, such as Beijing, Shanghai, Shenzhen, and Guangzhou. Our analysis highlights the magnitude and pace at which steel resources have been and are expected to be accumulated above ground. Our estimates capture the spatiotemporal dynamics of steel stocks, potentially allowing better policy-making and business decision-making on resource efficiency, waste management, and environmental sustainability on regional or urban scales.

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1. Introduction

The Anthropocene marks a new human-dominated geological epoch, over which human activity has profoundly affected the environment especially in the second half of the 20th century after World War II (Lewis and Maslin, 2015; Sterner et al., 2019). Driven by rapid industrialization and urbanization, large quantities of materials have been reallocated from in-ground ore deposits to the human-built environment, providing essential services to human's modern life. The amount of materials stocked in the built

environment is often referred to as *in-use stocks of materials* or *in-use material stocks* (Chen and Graedel, 2015). The expansion and maintenance of in-use material stocks (hereafter *material stocks*) enables economic prosperity, drives up material demand, and shapes socioeconomic metabolism patterns (Graedel and Cao, 2010; Greenfield and Graedel, 2013; Pauliuk et al., 2012a). More importantly, material stocks are regarded as future “urban mines” and can be potentially used for supplanting raw materials, thus allowing for less reliance on raw materials (Weisz et al., 2015). Unlike mineral ores, the location of material stocks changes rapidly due to urban expansion, economic growth, and technological development (Graedel et al., 2015; Song et al., 2019). Therefore, managing these future urban mines, of which the spatial dimension is less understood, calls for high-resolution maps of their location, quantity, and temporal changes (Rauch, 2009).

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The current progress of steel stocks estimation speaks to the need for better high-resolution mapping. Generally, two accounting methods, namely “top-down” and “bottom-up”, are used to estimate steel stocks (Gerst and Graedel, 2008; Song et al., 2020; Wang et al., 2015). The top-down method is able to estimate steel stocks by using the historical consumption of materials and a lifetime function (Pauliuk et al., 2012b, 2013; Wang et al., 2017), while the bottom-up method starts from counting every piece of steel-containing products, then investigates the steel intensity for each product, and finally adds up steel contained in all product categories (Han and Xiang, 2012; Liu et al., 2019; Song et al., 2020; Wang et al., 2015). Due to data availability, the top-down method is often limited to a global or national level. Whereas the bottom-up method offers a better understanding of steel stocks at a city level, this approach is labor-consuming and highly reliant on statistics.

Combining Geographical Information System (GIS) with bottom-up quantification provides a new path toward understanding the spatial distribution pattern of steel stocks on city scale. For example, Tanikawa et al. (2009) made the first attempt to investigate the spatial changes of steel stocks in urban areas. Thereafter, several GIS-based bottom-up accounting studies popped up for case urban areas (Mao et al., 2020; Lanau and Liu, 2020; Kleemann et al., 2017). Although this method characterizes the quantity of stocks in a high spatial resolution, it is challenging to use it to capture the spatial distribution pattern of stocks to a larger scale.

Satellite images and remote sensing (RS) data have been increasingly harnessed to generate geographically refined estimates of steel stocks on national or global scale. For example, nighttime light (NTL) images accessible from the Defense Meteorological Satellite Programs' Operational Line scan System (DMSP/OLS) have been used for estimating steel stocks (Liang et al., 2014, 2017; Yu et al., 2018), inspired by their use in energy consumption and CO₂ emissions estimation (Hu and Huang, 2019; Zhang et al., 2020). NTL images are especially useful when official statistics are scarce. However, the accuracy of NTL images is subject to its inherent limitations. First, the OLS sensor, which produces NTL images, cannot detect the light signals of hamlets where the values would be zero. Second, NTL pixels are usually saturated in the center of city areas where nighttime lights are very strong (Cao et al., 2019). Third, NTL images cannot capture physical systems that don't signal lights during nighttime, such as machinery, transportation facilities, domestic appliances, etc. In light of these limitations, estimates of steel stocks based on NTL images may be lower than the real quantity. Therefore, new indicators or approaches are needed for gridded steel stocks estimation to guarantee its accuracy.

In response to these knowledge gaps, we propose a new approach for steel stocks estimation, grounded on the gross domestic product (GDP), population (P), and built-up area (BUA), since previous studies suggested that steel stocks are positively correlated with GDP (Rauch, 2009), P (Huang et al., 2017), and BUA (Song et al., 2019). These three parameters' statistics and gridded data are available and can fully represent the impact of urbanization on steel stocks accumulation. We consider regional heterogeneity when applying this new approach and select mainland China to demonstrate the accuracy of the new approach in mapping steel stocks with a 1-km granularity over 1995–2015. We further project future steel stocks up to 2030 based on scenarios of GDP, P, and BUA. More specifically, we aim to address the following questions.

- (1) Where have steel stocks been accumulated over 1995–2015?
- (2) What would the spatial distribution of steel stocks be like in 2030?
- (3) What are the policy implications of high-resolution steel stocks mapping for resource management and sustainability?

2. Materials and methods

Taking advantage of the existing data from our previous study of steel stocks at the provincial level, we were able to correlate steel stocks with P, GDP, and BUA. As shown in Fig. 1, our new approach was implemented in three steps. First, multiple linear regression models were constructed between provincial statistics-based steel stocks, P, GDP, and BUA. Second, provincial steel stocks were downscaled to 1-km spatial resolution based on the resulting regression equations. The accuracy of the new approach was validated, and the spatiotemporal dynamics of steel stocks were explored. Third, the future spatial distribution pattern of steel stocks was projected based on the future scenarios of P, GDP, and BUA.

2.1. Database for provincial statistics-based steel stocks and socioeconomic indicators

Statistics-based steel stocks were sourced from pMAC (provincial Material Cycles and Manufactured Capital), which was constructed by Song et al. (2020) with consistent system boundaries, data sources, and modeling approaches. The time horizon of this dataset was from 1978 to 2018, and the spatial scale ranged from provinces to nation (Song et al., 2020). The steel stocks in this dataset were estimated by the bottom-up approach based on the identified 102 steel-containing products in each province and steel content of each product (Eq. (1)).

$$S_j(t) = \sum_i N_i(t) \times m_i(t) \quad (1)$$

where S_j is the steel stocks at the time t , measured in tonnes in the j th province; $N_i(t)$ is total number of product i in active use at time t ; and $m_i(t)$ is the steel content per-unit of product i .

The quantity of steel-containing products was sourced from the Statistical Yearbooks of each province. Steel content was estimated based on various sources and assumptions such as expert judgments. The steel stocks in each province can be divided into five end-use sectors, including buildings, infrastructure, transportation facilities, machinery, and domestic appliances. For this study, we used the aggregate information on provincial scale during 1995–2018. Fig. 2 gave an overview of the provincial steel stocks generated by the database (see the Supporting Material and Song et al. (2020) for details).

Three socioeconomic indicators, P, GDP, and BUA, were chosen for constructing multiple linear regression with steel stocks. Statistical data for P, GDP, and BUA during 1995–2018 were extracted from the Statistical Yearbook of each province.

2.2. Development of multiple linear regression models

We opted to use multiple linear regression, as suggested by previous studies (Rauch, 2009; Song et al., 2019), to capture the

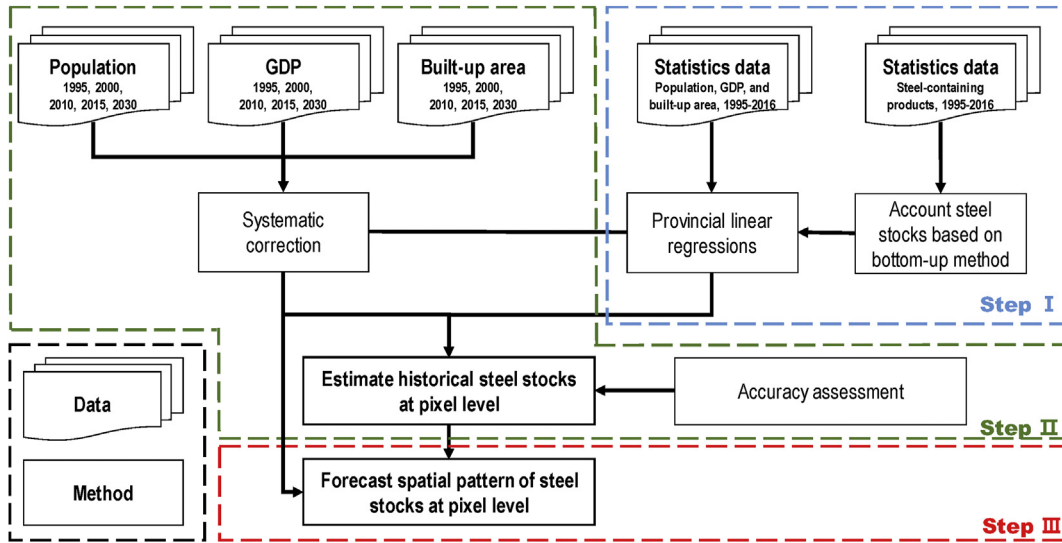


Fig. 1. Methodological framework of gridded steel stocks estimation.

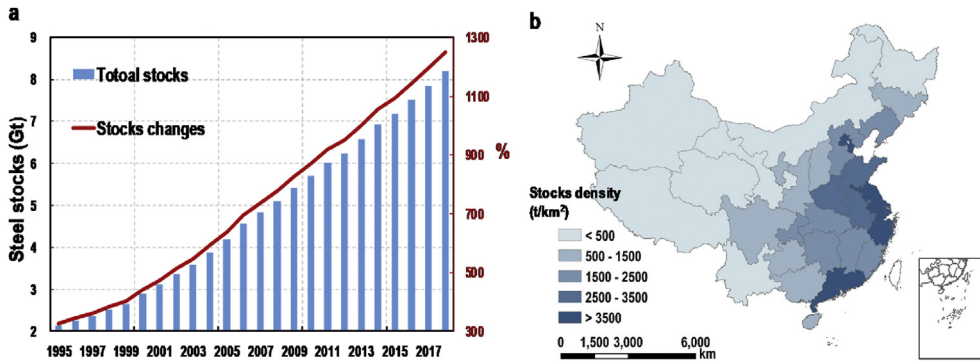


Fig. 2. Total steel stocks in mainland China during 1995–2018 (a) and stocks density for 31 provinces in 2018 (b).

relationship between steel stocks, P, GDP, and BUA at provincial level (Eq. (2)). We used statistics-based steel stocks during 1995–2014 to construct the regression models, and steel stocks during 2015–2018 were used to validate the model performance.

$$S_j = b_{1,j}P_j + b_{2,j}GDP_j + b_{3,j}BUA_j + c_j \quad (2)$$

where S_j is the steel stocks estimated by Eq. (1) in the j th province. P_j , GDP_j , and BUA_j are P (unit: people), GDP (unit: CNY), and BUA (unit: km^2) at j th province. $b_{1,j}$, $b_{2,j}$, and $b_{3,j}$ are the fitted slope coefficients of P, GDP, and BUA at the j th province, respectively. c_j is the fitted intercept coefficient of multiple linear regression model at the j th province. Since the BUA in Tibet has changed dramatically after 2012, c_j has been introduced to correct the accuracy of the model. The other 30 provinces' regression model does not contain c_j .

2.3. Downscaling steel stocks

Modeled data during 2015–2018 were used to compare with statistics-based steel stocks with Pearson's correlation coefficient (Pearson, 1895), which was a traditional method of estimating modeled exponents recommended by previous studies (Crow et al., 2000; Deidda, 2000). The formula of Pearson's correlation coefficient is as follows.

$$\text{Cor.} = \frac{\sum_{j=1}^n (S_{m,j} - \overline{S_{m,j}})(S_j - \overline{S_j})}{\sqrt{\sum_{j=1}^n (S_{m,j} - \overline{S_{m,j}})^2} \sqrt{\sum_{j=1}^n (S_j - \overline{S_j})^2}} \quad (3)$$

where Cor. represents the Pearson's correlation coefficient, n is the number of included provinces in mainland China (i.e., $n = 31$), S_j is described above, $S_{m,j}$ is modeled stocks in the j th province, $\overline{S_{m,j}}$ and $\overline{S_j}$ are the average value of $S_{m,j}$ and S_j , respectively.

Based on the multiple linear regression equations constructed above, we were able to downscale the steel stocks at a 1-km grid level. Gridded P, GDP, and BUA data with a spatial resolution of 1-km in China in 1995, 2000, 2005, 2010, and 2015 were obtained from the Resources and Environmental Sciences Data Center, Chinese Academy of Sciences (RESDC). All the pixels that are either negative fitted values or not built-up area were set as zero. Furthermore, we used the equation recommended by Meng et al. (2017) to correct the pixel-level estimation, ensuring that the sum of the gridded steel stocks within the boundary of a province equals its statistics-based steel stocks:

$$S'_{pix} = \widehat{S}_{pix} \times \frac{S_j}{\widehat{S}_{p,j}} \quad (4)$$

where S'_{pix} is the downscaled stocks; S_j is the statistics-based steel stocks; $\hat{S}_{p,j}$ is the sum of pixel-level estimated stocks (\hat{S}_{pix}) within j th province.

2.4. Projection of steel stocks

To project the future 1-km gridded steel stocks, we based ourselves on the premise that the relationship between steel stocks, P, GDP, and BUA will not change till 2030. This assumption is in line with the conclusions that the utilization of steel in China will follow an increasing trajectory before entering the flatten-off pattern similar to that observed in industrialized countries (Müller et al., 2006; Pauliuk et al., 2012b; Song et al., 2020). From previous studies, we concluded that once per-capita steel stocks in China have crossed a threshold at ~ 2 t (tonnes) around 1995, it entered a period of very strong and sustained increasing pattern till 2030 (Song et al., 2020). Hence, based on the constructed multiple linear regressions, we projected the gridded steel stocks in 2030.

Gridded BUA in 2030 was used the database projected by Zhou et al. (2019), which was a resolution of 30 arc-seconds (approximately 1-km at the equator) containing urban growth probabilities. This dataset was constructed by considering the topography, traffic networks, protected areas, water bodies, and historical urban developing features. In this study, we defined all the grids whose urban growth rate was more than the specific threshold values as the built-up area. Therefore, three classes of scenarios with three specific threshold values were developed in our study (Table 1). Gridded P in 2030 was obtained from the Socioeconomic Data and Applications Center (SEDAC) of NASA, which was downscaled based on the Shared Socioeconomic Pathways (SSPs) at 1-km resolution and include five scenarios (SSP1–SSP5) (Gao, 2017, 2019) (Table 1). The SSPs were developed to support future climate and global change research and the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6). Gridded P projections were consistent with SSPs and were important for understanding the spatial distribution of SSPs. Provincial gridded GDP was predicted by the first-order difference and ARIMA models (Harvey, 1993; Jones, 1980; Mascaro et al., 2014) based on the provincial historical development pattern. Three scenarios were considered through the estimation of GDP growth-as-usual and its 95% confidence interval (CI) (Table 1). Overall, there were 45 scenarios according to the three parameters scenario definition (see details in Table S4 in the Supporting Material).

3. Results

3.1. Linear regressions

We first analyzed the correlations between steel stocks and three socioeconomic variables in each province, and the results

showed that P, GDP, and BUA significantly correlated with steel stocks. For example, steel stocks in Shanghai were well correlated with P ($R^2 = 0.98$, $p < 0.001$), GDP ($R^2 = 0.96$, $p < 0.001$), and BUA ($R^2 = 0.94$, $p < 0.001$) (Fig. 3). A multiple linear regression model was then set up between steel stocks and these three variables, which had high goodness-of-fit with R^2 of 0.99 ($p < 0.001$). Similarly, regression models for each province were constructed. The R^2 values of these models were more than 0.90 ($p < 0.001$), and most of the coefficients were significant at a 95% confidence (Table S2).

A strong linear relationship was detected between the modeled and the statistics-based steel stocks for 31 provinces during 2015–2018 (Fig. 4a–d, average Cor. = 0.995), and most of the scattered points were uniformly distributed along the 1:1 line. This result indicated that the constructed regression model was robust in deriving steel stocks at the grid level.

3.2. Historical spatial distribution of steel stocks

Driven by rapid industrialization and urbanization, massive steel stocks have been accumulated in the built environment. Nationally, the steel stocks have risen 4-fold over the past 23 years, increasing from 2.2 to 8.2 Gt (gigatonnes). Spatially, the steel stocks were widely distributed in human settlements across mainland China. The distribution, however, was unbalanced. The dense population, crowded buildings, and massive infrastructure made eastern China having higher stocks density. In contrast, western China had sparse steel stocks density due to its lower degree of urbanization and slower economic growth. During 1995–2015, the steel stocks have experienced a dramatic spatial expansion (Fig. 5b). In 1995, the average of steel stocks was only 12,873 t/km², ranging from 2,005 to 85,236 t/km² with more steel stocks accumulated in few big cities, such as Beijing, Shanghai, Chengdu, Guangzhou, and Shenzhen (Fig. S2). The steel stocks increased to 33,027 t/km² in 2015, ranging from 9,716 to 88,485 t/km² with high density in metropolitan areas and provincial capital (Fig. 5a).

Similar to urban clusters, four steel stocks clusters can be identified in the gridded map, including the Beijing-Tianjin-Hebei (Jing-Jin-Ji) agglomeration, Yangtze River Delta (YRD), Guangdong-Hong Kong-Macao Greater Bay Area (GBA), and Chengdu-Chongqing metropolitan (CCM), where drastic urbanization is taking place. These clusters possessed over 40% of national steel stocks in 2015 and became clearly the most important stocks deposits (Fig. 6). During 1995–2015, there were obvious spatial expansion and stock increases in urban centers than suburban areas in these four clusters (Fig. S9). The steel stocks in Jing-Jin-Ji varied from 10,748 to 50,755 t/km² with an average of 26,269 t/km² in 2015, and had evolved in a hub-spoke spatial development pattern. Beijing and Tianjin were the dominant cities in this cluster, working as nodes at the top hierarchy (Fig. 6a–b). The steel stocks in YRD had demonstrated a belt development pattern, and reached an average of 37,383 t/km² in 2015, ranging from 20,233 to 73,708 t/

Table 1
Parameters and scenarios for future projection.

Scenarios number	Parameters			Scenarios definition
	Population (P)	Built-up area (BUA)	Gross domestic product (GDP)	
1	SSP1 (Sustainability)	Urban growth rate ≥ 0	GDP growth-as-usual	2030P1B3G2 (Minimal stocks)
2	SSP2 (Middle of the road)	Urban growth rate $\geq 50\%$	Lower endpoint of 95% CI	2030P4B2G1 (Baseline)
3	SSP3 (Regional rivalry)	Urban growth rate $\geq 80\%$	Upper endpoint of 95% CI	2030P3B1G3 (Maximal stocks)
4	SSP4 (Inequality)	–	–	–
5	SSP5 (Fossil-fueled development)	–	–	–

SSP is the Shared Socioeconomic Pathways; CI is the confidence interval for the GDP growth-as-usual scenario; P, B, and G represent the population, built-up area, and gross domestic product, respectively. The numbers represent five different scenarios. For example, 2030P1B3G2 means P in scenario SSP1, BUA growth rate $\geq 0\%$, and GDP growth at the lower endpoint of 95% CI of GDP growth-as-usual.

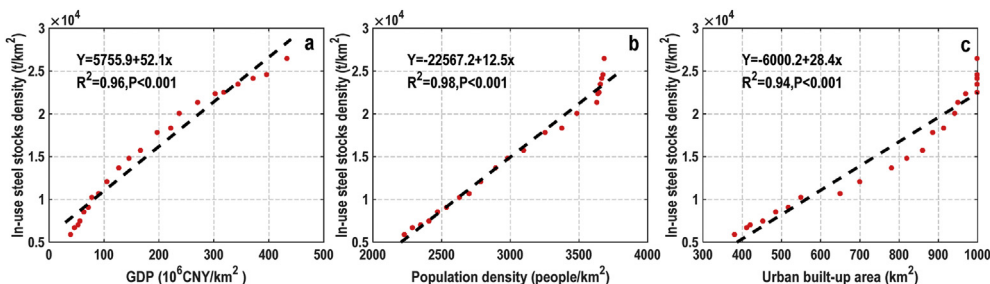


Fig. 3. Relationship of in-use steel stocks density with GDP (a), population (b), and built-up area (c) for Shanghai.

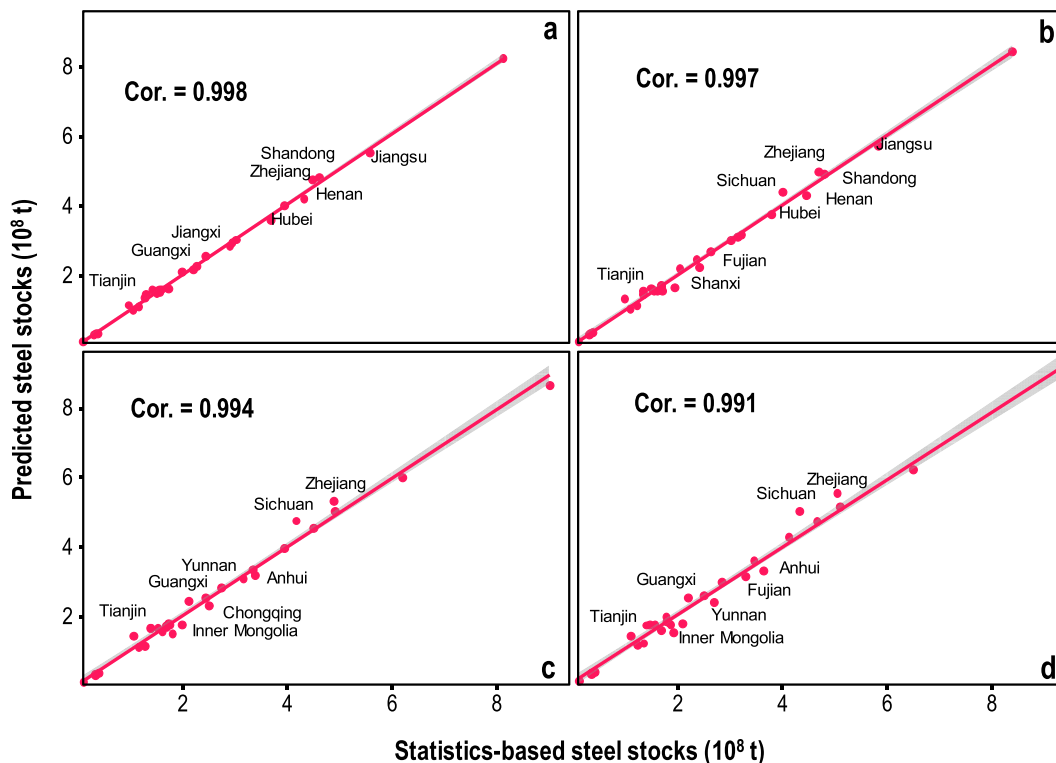


Fig. 4. Comparisons between predicted and statistics-based steel stocks in 2015 (a), 2016 (b), 2017 (c), and 2018 (d). The gray shading represents 99% confidence intervals of the log-log regression.

km². This cluster was dominated by Shanghai, with Nanjing and Hangzhou acting as supporting cities. The steel stocks in GBA, which lay between 67,941 and 72,489 t/km² with an average of 69,183 t/km² in 2015, features an inter-locking hub pattern. The CCM had the highest stocks density (up to 88,485 t/km² in 2015) due to its dense population and demonstrated a dual-core steel stocks growth structure. The dominant cities, Chengdu and Chongqing, were strong enough to function as major steel stocks growth poles.

3.3. Looking to the future of steel stocks

At the provincial level, steel stocks were projected to keep increasing up to 2030. Across scenarios, the national sum of steel stocks will reach an average of 9.0 Gt, ranging from 5.5 to 12.5 Gt (Fig. S7). The wide range of our projections reflects the uncertainties of underlying drivers. Population growth pattern had a more significant impact on steel stocks, and the urban growth rate had a broader impact on the spatial expansion of steel stocks.

Spatially, the average steel stocks will increase to 64,636 t/km² (Base-scenario, 2030P3B2G1), varying from 24,724 km² (low P, low GDP, and less BUA scenario, 2030P1B3P2) to 159,877 km² (high P, high GDP, and more BUA scenario, 2030P3B1G3) (Fig. 7). The steel stocks in scenario 2030P1B3G2 were lowest, ranging from 22,555 to 135,333 t/km², and the increase of steel stocks was limited due to a shrinking population of SSP1 and a lower urban growth rate. In contrast, the steel stocks in scenario 2030P3B1G3 were highest, and the combined effect of P, GDP, and BUA led to 80,238–320,954 t/km² of steel stocks in 2030.

The high-speed railway network, highways, waterways, airport, and other projects have bolstered the city clusters and connected many of the first-, second-, and third-tier cities within the city clusters, which result in the steel stocks continuing expansion in 2030 (Fig. S9). In addition to the increasing steel stocks of existing cities, new stocks deposits are beginning to emerge in established clusters. For the 2030P3B1G3 scenario, the steel stocks will dramatically increase with deepening urbanization. The steel stocks in Jing-Jin-Ji will reach to 30,304 t/km² in 2030 (ranging

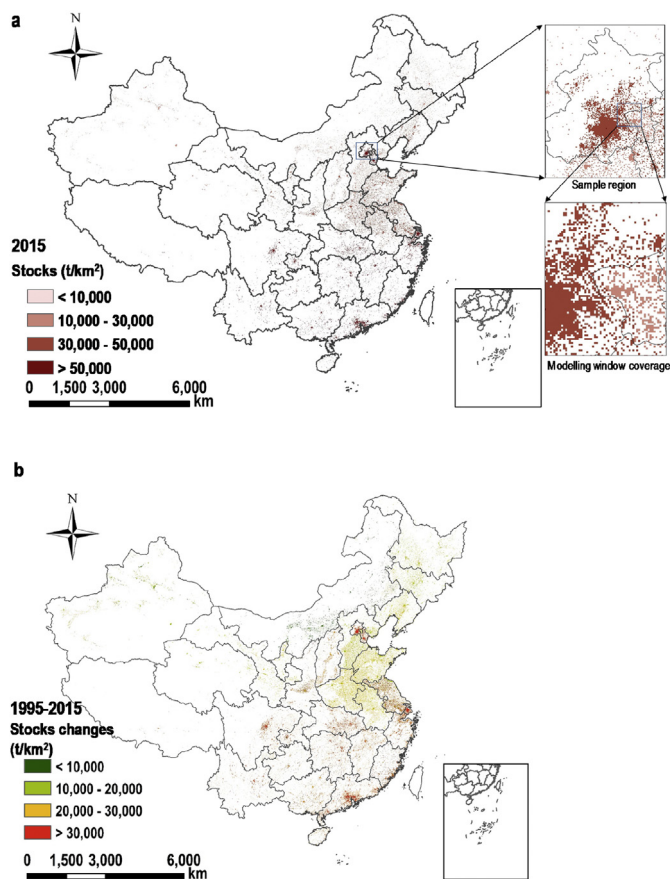


Fig. 5. National coverage of in-use steel stocks in 2015 at 1×1 km grid level and an example (in a partial view) of modelling area (a), and stocks changes during 1995–2015 (b).

from 1,343 to 342,594 t/km²), and the established and reinforced connections between cities will attract more materials accumulated in second-tier cities of this region, including Shijiazhuang and Baoding. The steel stocks in the YRD and GBA cluster will be 34,347 t/km² (ranging from 2,256 to 291,042 t/km²) and 20,556 t/km² (ranging from 478 to 121,981 t/km²) respectively in 2030, and there will be a widening trend of steel stocks gap between major and node cities based on the highly developed infrastructure. The steel stocks in CCM will get to 20,851 t/km² (ranging from 538 to 137,372 t/km²) in 2030, with more stocks accumulated around the major growth poles.

Based on the projection, new steel stocks clusters can be identified, including Shandong Peninsula, Central Plain, and Yangtze Mid-River clusters. These clusters that used to be in the preliminary stages of development in 2015 have grown to be large deposits of steel stocks. For example, steel stocks in the Central Plain cluster lie between 12,225 and 14,652 t/km² in 2030 (Fig. 7).

4. Discussion

4.1. Robustness and limitations of our estimation

Our study provides a more nuanced approach of retrospective and prospective steel stocks at a high-resolution level (1-km), and the results show a robust and integrated gridded steel stocks estimation based on P, GDP, and BUA. By comparing our modeled steel stocks in some selected cities and years with those from existing literature estimates, which are derived from a bottom-up approach,

the robustness and reliability of our proposed method can be validated. At the urban level, our estimates are generally higher, and the difference is within a range of 30% (Table 2). Taking Xiamen as an example, our estimate is 27% bigger than that evaluated by Song et al. (2019). The amount of steel-containing products is the main reason for the difference, since only 55 steel-containing products were identified in Song et al. (2019). Furthermore, steel intensity estimated by different studies can bring uncertainties to the results. At the pixel level, our estimates are in great agreement with estimates in Yu et al. (2018) and Han et al. (2018), and the differences are within 5%. Moreover, the strong linear relationship between the modeled and statistics-based steel stocks on the provincial scale (Fig. 4) also supports the theoretical accuracy of our model. At the national level, the distribution pattern of steel stocks estimated by our study is in good accordance with previous studies (Liang et al., 2017; Rauch, 2009; Yu et al., 2018). Moreover, our estimates of steel stocks in 2030 lie between 5.5 and 12.5 Gt (based on 45 scenarios), which is in good accordance with ~8–12 Gt (based on 6 scenarios) forecasted by Pauliuk et al. (2013).

Our results bear unavoidable limitations that could be further improved in the future. First, the scale effect occurs when downscaling the stocks from the provincial levels to pixel levels. Although our results are at the best resolution of 1-km under the current circumstances, the lack of primary data at higher resolutions does not lead to full verification. Second, it should be noted that the projection for steel stocks involves large uncertainties due to the large uncertainties of underlying drivers, which was proved by previous studies (Pauliuk et al., 2013). The projection is not actual numbers, but the spatial distribution patterns and trends that are reproduced under many different parameters assumptions and scenarios. Third, our proposed method is not a comprehensive model for downscaling steel stocks growth but, rather, represents the assumed extension of the steel stocks development that occurred during 1995–2030. Although we have included major factors, including P, GDP, and BUA when downscaling steel stocks, the real story may be much more complicated than this. The complex structure of steel stocks growth depends on many more predictable and unpredictable factors, which are not considered in this study, such as national and provincial economy, investment policy, regional development regulations, industrial structure, and purchasing power of residents, etc. In the future, with the emergence and development of big data science and machine learning, it might be possible to obtain spatial data for the aforementioned variables and construct regression models between steel stocks and those variables, thereby enhancing the performance of pixel-level steel stocks estimation.

Based on the increasing availability of global coverage of spatial data for population and land use, for example, 100-m population data provided by Guanghan et al. (2016) and Global Land Project's land use and cover maps with 30-m resolution (NGCC, 2019), our proposed method could also be applied to other countries, regions, and different materials stocks (e.g., cement and aluminum) at higher resolution in the future.

4.2. Policy implications for resource management and sustainability

The retrospective and prospective gridded map of stocks provide more than a visual aid for understanding how human society redistributed in-ground resources. More importantly, understanding the locations and sizes of anthropogenic resource reservoirs at a relatively high-spatial-resolution facilitates the promotion of efficient policies of material management and urban sustainable development.

Resource recycling through urban mines plays an important role

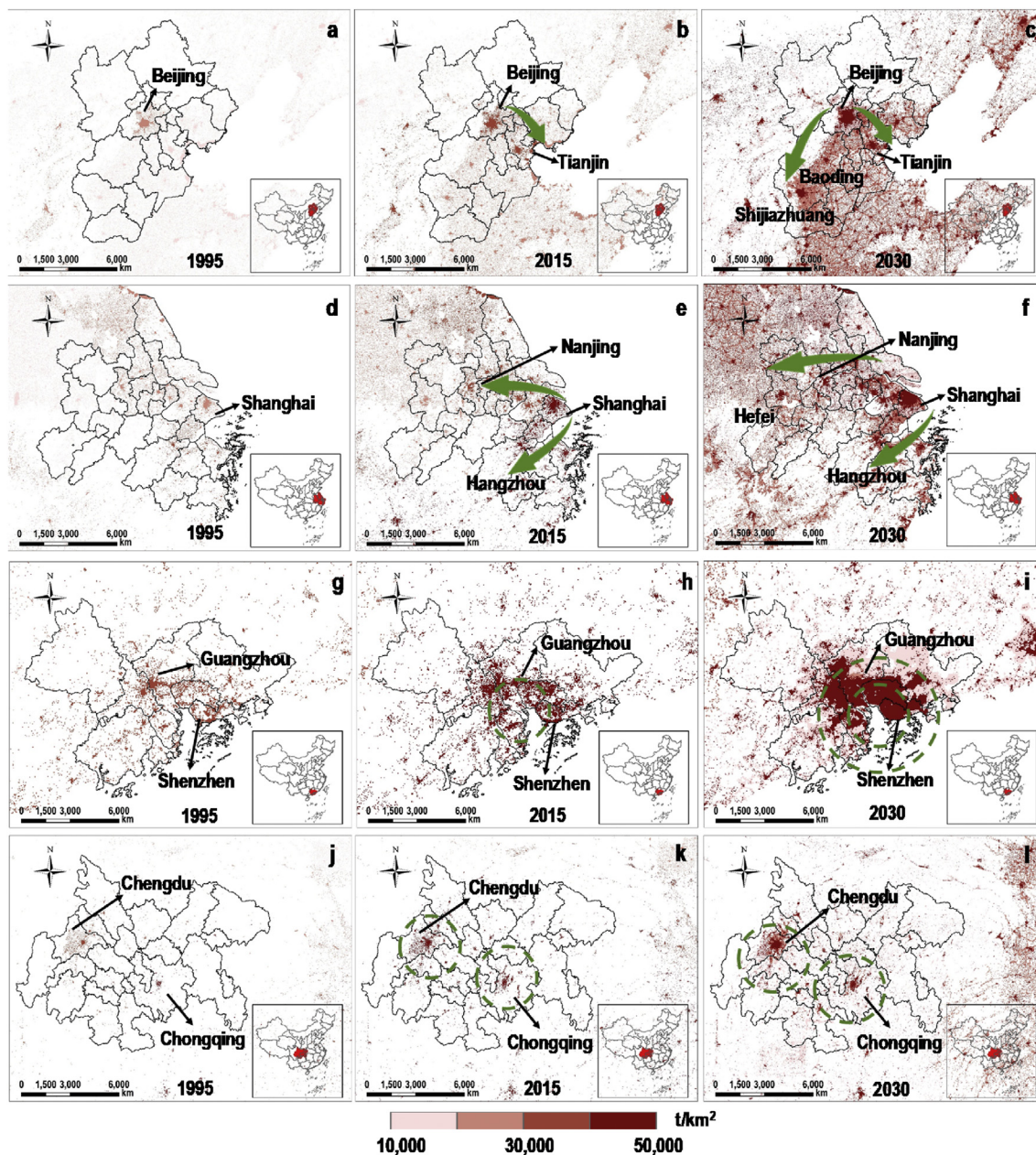


Fig. 6. Gridded mapping of in-use steel stocks in 1995, 2015, and 2030 for selected areas: Beijing-Tianjin-Hebei agglomeration (a, b, and c), Yangtze River Delta (d, e, and f), Guangdong-Hong Kong-Macao Greater Bay Area (g, h, and i), and Chengdu-Chongqing metropolitan (j, k, and l). The green arrow or circle denotes the spatial expansion direction or pattern of steel stocks.

in the implementation of circular economy and emission reduction policies (Morfeldt et al., 2015; Tian et al., 2018). As the largest consumer of steel (World Steel Association, 2019), China has created intense pressure on global demand for steel and is taking action in promoting waste recirculation (Mathews and Tan, 2016). Yet, the quantity and location of urban mines remain poorly understood. Identified as mines of secondary materials (Jacobs, 1961), the steel stocks deposits evaluated by our study dictate its potential for recovery at a high-resolution. As shown in Fig. 5, the long-term planning of resources discards management networks should focus on developed urban agglomerations, e.g. Jing-Jin-Ji agglomeration. Notably, the existing huge steel stocks deposits in core cities, including Beijing, Shanghai, and Guangzhou, will firstly create opportunities to promote scrap recycling, implement closed steel

cycles, and efficiently pursue a zero-waste city plan. However, the average construction and demolition waste recovery rate is extremely low in China, at only 5% (Han et al., 2018), which calls for intensive attention for effectively waste-management policies. Furthermore, the government and secondary steel makers can better implement recovery plans according to the gridded information in 2030, although producing high-quality steel from different constituents of scrap could be a challenge (Rong and Lahdelma, 2008). Given the identified locations of steel stocks increases between the present and 2030 (Fig. S9), steelmakers can better control new additions to production capacity, planning investments in primary and secondary production operations to minimize total cost, increase the efficiency of industries, and reduce the carbon footprint of steel product.

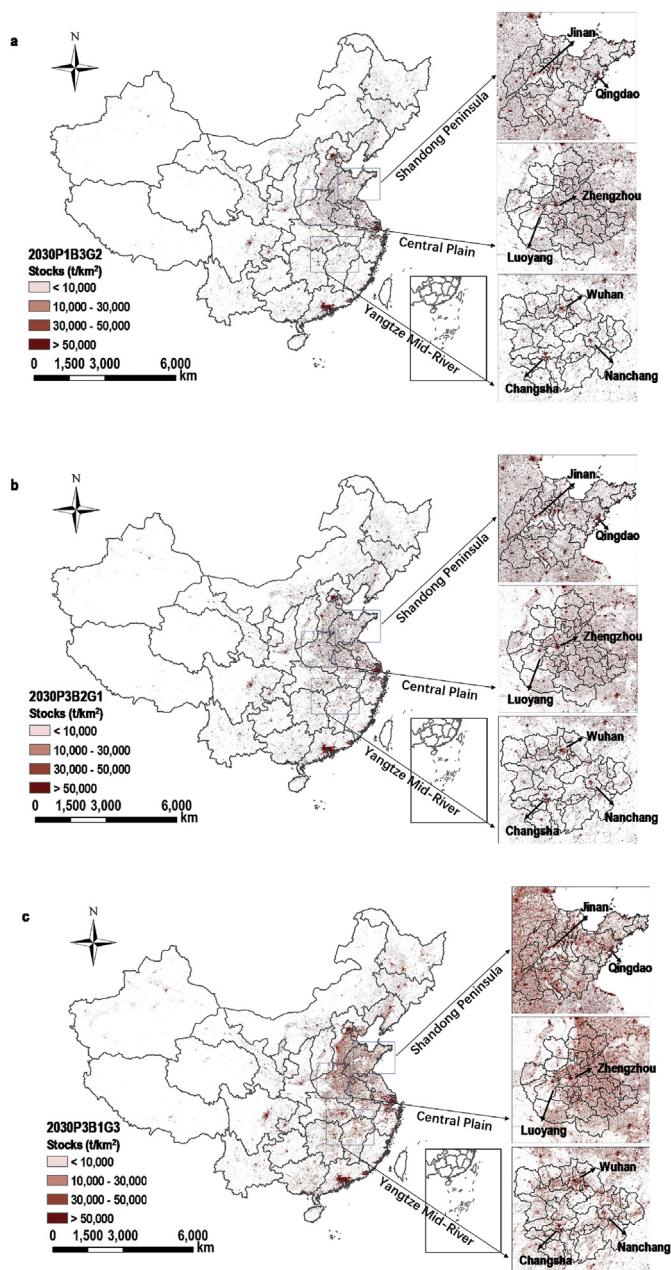


Fig. 7. Gridded mapping of in-use steel stocks in 2030P1B3G2 (a), 2030P3B2G1 (b), and 2030P3B1G3 (c) in 2030. P, B, and G represent the population, built-up area, and gross domestic product, respectively. Numbers represent the different scenarios in Table 1. For example, 2030P1B3G2 means P in scenario SSP1, BUA growth rate $\geq 50\%$, and GDP growth at the lower endpoint of 95% confidence interval of GDP growth-as-usual.

Stocks growth speed and pattern vary in different urban. By highlighting the relationships between economic growth, urban expansion, population increase, and material utilization (Fig. 3), our results reveal that the stocks accumulation pattern in developed cities on a more refined level could provide benchmarks for the less-developed cities. For example, new steel stocks clusters can be generated in 2030 (e.g., Shandong Peninsula) by following the development pattern of well-established clusters in 2015 with further urban expansion and population growth, and the new steel stocks (net stocks) tend to be accumulated in the city center, which is generally 3-fold higher than that in the outskirts (Fig. S8b). On the national scale, deepening urbanization will continuously drive

as much as ~5 Gt steel stocks to be accumulated in urban areas, since more constructions will be needed to support an increase of over 1.3 billion people living in urban by 2030 (United Nations, 2018). The identified stocks accumulation pattern is crucial to properly plan the urban system planning strategies based on national “One-Belt, Seven-Axes, and Multiple-Channels” planning (Fang and Yu, 2017) and China’s New Infrastructure Planning. Most of the current urban clusters are in their preliminary stages with the incorporated surrounding cities, usually sharing physical or economic links (Keuschnigg et al., 2019). Our high-resolution maps with the quantity and location of steel stocks could inform the government planners and urban designers in their decision-making on the capacity and effective planning to match with the urban agglomeration development.

Material stocks are key in attaining sustainability (Weisz et al., 2015). Improving material stocks productivity to reduce its resources and environmental impacts, while delivering services for human well-being, will be essential for urban sustainable development (Hertwich et al., 2019; Zhang et al., 2018). Generally, increasing the stocks density is an effective strategy to increase the productivity (Pauliuk and Müller, 2014; Weisz et al., 2015; Zhang et al., 2018). Our results show that the high density of steel stocks in large cities (e.g., Beijing and Shanghai) can provide services to more people to maintain higher productivity (Fig. 3b). However, the productivity of stocks is difficult to be improved once they have been accumulated, because the services generated by the products will be “lock-in”, especially for those long lifespans of steel-containing products, such as buildings and infrastructure (Zhang et al., 2017). Actually, China is planning to build ~40 billion square meters of floor space, requiring the construction of 20,000–50,000 new skyscrapers over the next 20 years (Ellen MacArthur Foundation, 2018). Given the scenarios for future net stocks spatial location (Fig. S8), the long-lived resource-intensive constructions should be avoided during the urban expansion. Developing a compact city and implementing green infrastructure strategies are crucial in improving the stocks productivity, which is important to achieve carbon neutrality in the future

Issues of sustainability now raise their heads, because the balance between resource demand and ultimate supply must be considered. Detailed information on material stocks above-ground as well as under-ground (e.g., tunnels and pipelines) is badly needed in the future. Researches on the spatial distribution of discard are also strongly needed. The results of the present work could then be extended, thereby forming a much fuller picture of metal extraction, use, loss, and long-run sustainability.

5. Conclusions

By constructing linear regression models between provincial statistics-based steel stocks and population, gross domestic product, and built-up area, this paper proposed a more nuanced approach to evaluate the retrospective and prospective performance of steel stocks at a high-resolution level. China was selected as a case to validate the accuracy of the proposed methods and to increase our understandings of its spatiotemporal dynamics of steel stocks during 1995–2030.

Our results illustrate that the proposed method provides a useful and fast estimation for gridded steel stocks. It can be applied to forecast the future spatial distribution of steel stocks and shows great potential to be applied as a proxy of many other materials stocks, especially those in regions where there is a lack of sufficient and reliable statistical data. The gridded mapping of steel stocks found that stocks in metropolitan areas and provincial capitals are much higher than those in other regions. Steel stocks in Beijing-Tianjin-Hebei agglomeration, Yangtze River Delta, Guangdong-

Table 2
Comparison between our results and previous estimates.

City/Region	Year	Earlier estimates	This study	Difference
Handan	2005	13 Mt (Lou and Shi, 2008)	15 Mt	15%
Xiamen	2015	11 Mt (Song et al., 2019)	14 Mt	27%
Guangzhou	2015	42 Mt (Liu et al., 2019) ^a	46 Mt	10%
Shenzhen	2015	40 Mt (Liu et al., 2019) ^a	43 Mt	8%
Nanjing	2015	35 Mt (Liu et al., 2019) ^a	38 Mt	9%
Wuhan	2015	34 Mt (Liu et al., 2019) ^a	39 Mt	15%
Chengdu	2015	48 Mt (Liu et al., 2019) ^a	45 Mt	6%
Shenyang	2015	20 Mt (Liu et al., 2019) ^a	22 Mt	10%
Shanghai	2010	43,000 t/km ² (Han et al., 2018)	44,180 t/km ²	3%
China	2008	~270 Mt on average (Yu et al., 2018)	268 Mt	1%
China	2008	~300 Mt on average (Liang et al., 2014)	268 Mt	11%

^a Steel stocks in the urban area (excluding sub-urban area) of the city.

Hong Kong-Macao Greater Bay Area, and Chengdu-Chongqing metropolitan have more stocks density than other cities. By 2030, with the deepening of urbanization, Shandong Peninsula, Central Plain, and Yangtze Mid-River clusters will be new hubs of steel stocks. These findings may increase our understanding of the spatiotemporal dynamics of steel stocks and support sustainable development in resource management.

CRediT authorship contribution statement

Lulu Song: Writing – original draft, Methodology, Software, Writing – review & editing. **Shaoqing Dai:** Software. **Zhi Cao:** Writing – review & editing. **Yupeng Liu:** Writing – review & editing. **Wei-Qiang Chen:** Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Cao, X., Hu, Y., Zhu, X., Shi, F., Zhuo, L., Chen, J., 2019. A simple self-adjusting model for correcting the blooming effects in DMSP-OLS nighttime light images. *Remote Sens. Environ.* 224, 401–411.

Chen, W.Q., Graedel, T.E., 2015. In-use product stocks link manufactured capital to natural capital. *Proc. Natl. Acad. Sci. U. S. A.* 112 (20), 6265–6270.

Crow, W.T., Wood, E.F., Dubayah, R., 2000. Potential for downscaling soil moisture maps derived from spaceborne imaging radar data. *J. Geophys. Res. Atmos.* 105 (D2), 2203–2212.

Deidda, R., 2000. Rainfall downscaling in a space-time multifractal framework. *Water Resour. Res.* 36 (7), 1779–1794.

Ellen MacArthur Foundation, 2018. The circular economy opportunity for urban and industrial innovation in China. <https://www.ellenmacarthurfoundation.org/publications/chinareport#cn-report>.

Fang, C., Yu, D., 2017. Urban agglomeration: an evolving concept of an emerging phenomenon. *Landsc. Urban Plann.* 162, 126–136.

Gao, J., 2017. Downscaling Global Spatial Population Projections from 1/8-degree to 1-km Grid Cells. NCAR Technical Note NCAR/TN-537+STR.

Gao, J., 2019. Global Population Projection Grids Based on Shared Socioeconomic Pathways (SSPs), Downscaled 1-km Grids, 2010–2100. NASA Socioeconomic Data and Applications Center (SEDAC), Palisades, NY.

Gerst, M.D., Graedel, T.E., 2008. In-use stocks of metals: status and implications. *Environ. Sci. Technol.* 42 (19), 7038–7045.

Graedel, T.E., Cao, J., 2010. Metal spectra as indicators of development. *Proc. Natl. Acad. Sci. U. S. A.* 107 (49), 20905–20910.

Graedel, T.E., Harper, E.M., Nassar, N.T., Reck, B.K., 2015. On the materials basis of modern society. *Proc. Natl. Acad. Sci. U. S. A.* 112 (20), 6295–6300.

Greenfield, A., Graedel, T.E., 2013. The omnivorous diet of modern technology. *Resour. Conserv. Recycl.* 74, 1–7.

Han, J., Xiang, W.-N., 2012. Analysis of material stock accumulation in China's infrastructure and its regional disparity. *Sustain. Sci.* 8 (4), 553–564.

Han, J., Chen, W.Q., Zhang, L., Liu, G., 2018. Uncovering the spatiotemporal dynamics of urban infrastructure development: a high spatial resolution material stock and flow analysis. *Environ. Sci. Technol.* 52 (21), 12122–12132.

Harvey, A.C., 1993. *Time Series Models*. Harvester Wheatsheaf.

Hertwich, Edgar G., et al., 2019. Material efficiency strategies to reducing greenhouse gas emissions associated with buildings, vehicles, and electronics—a review. *Environ. Res. Lett.* 14, 043004.

Hu, T., Huang, X., 2019. A novel locally adaptive method for modeling the spatiotemporal dynamics of global electric power consumption based on DMSP-OLS nighttime stable light data. *Appl. Energy* 240, 778–792.

Huang, C., Han, J., Chen, W.Q., 2017. Changing patterns and determinants of infrastructures' material stocks in Chinese cities. *Resour. Conserv. Recycl.* 123, 47–53.

Jacobs, J., 1961. *The Death and Life of Great American Cities*. Vintage.

Jones, R.H., 1980. Maximum likelihood fitting of ARMA models to time series with missing observations. *Technometrics* 22 (3), 389–395.

Keuschnigg, M., Mutgan, S., Hedström, P., 2019. Urban scaling and the regional divide. *Sci. Adv.* 5 (1), eaav0042.

Kleemann, F., Lederer, J., Rechberger, H., Fellner, J., 2017. GIS-based analysis of Vienna's material stock in buildings. *J. Ind. Ecol.* 21, 368.

Lanau, M., Liu, G., 2020. Developing an urban resource cadaster for circular economy: a case of Odense, Denmark. *Environ. Sci. Technol.* 54 (7), 4675–4685.

Lewis, S.L., Maslin, M.A., 2015. Defining the anthropocene. *Nature* 519 (7542), 171–180.

Liang, H., Tanikawa, H., Matsuno, Y., Dong, L., 2014. Modeling in-use steel stock in China's buildings and civil engineering infrastructure using time-series of DMSP/OLS nighttime lights. *Rem. Sens.* 6, 4780–4800.

Liang, H., Dong, L., Tanikawa, H., Zhang, N., Gao, Z., Luo, X., 2017. Feasibility of a new-generation nighttime light data for estimating in-use steel stock of buildings and civil engineering infrastructures. *Resour. Conserv. Recycl.* 123, 11–23.

Liu, Q., Cao, Z., Liu, X., Liu, L., Dai, T., Han, J., Duan, H., Wang, C., Wang, H., Liu, J., Cai, G., Mao, R., Wang, G., Tan, J., Li, S., Liu, G., 2019. Product and metal stocks accumulation of China's megacities: patterns, drivers, and implications. *Environ. Sci. Technol.* 53, 4128–4139.

Lou, Y., Shi, L., 2008. Analyzing iron and aluminum stocks in Handan city in 2005 (in Chinese). *Resour. Sci.* 30 (1), 147–152.

Mao, R., Bao, Y., Huang, Z., Liu, Q., Liu, G., 2020. High-resolution mapping of the urban built environment stocks in Beijing. *Environ. Sci. Technol.* 54 (9), 5345–5355.

Mascaro, G., Vivoni, E.R., Gochis, D.J., Watts, C.J., Rodriguez, J.C., 2014. Temporal downscaling and statistical analysis of rainfall across a topographic transect in northwest Mexico. *J. Appl. Meteorol. Climatol.* 53, 910–927.

Mathews, J.A., Tan, H., 2016. Circular economy: lessons from China. *Nature* 531 (7595), 440–442.

Meng, X., Han, J., Huang, C., 2017. An improved vegetation adjusted nighttime light urban index and its application in quantifying spatiotemporal dynamics of carbon emissions in China. *Rem. Sens.* 9, 829.

- Morfeldt, J., Nijs, W., Silveira, S., 2015. The impact of climate targets on future steel production—an analysis based on a global energy system model. *J. Clean. Prod.* 103, 469–482.
- Müller, D.B., Wang, T., Duval, B., Graedel, T.E., 2006. Exploring the engine of anthropogenic iron cycles. *Proc. Natl. Acad. Sci. U. S. A* 103 (44), 16111–16116.
- NGCC, 2019. Global Land Cover Mapping at 30 M Resolution.
- Pauliuk, S., Müller, D.B., 2014. The role of in-use stocks in the social metabolism and in climate change mitigation. *Global Environ. Change* 24, 132–142.
- Pauliuk, S., Dhaniati, N.M.A., Müller, D.B., 2012a. Reconciling sectoral abatement strategies with global climate targets : the case of the Chinese passenger vehicle fleet. *Environ. Sci. Technol.* 46, 140–147.
- Pauliuk, S., Wang, T., Müller, D.B., 2012b. Moving toward the circular economy: the role of stocks in the Chinese steel cycle. *Environ. Sci. Technol.* 46 (1), 148–154.
- Pauliuk, S., Milford, R.L., Müller, D.B., Allwood, J.M., 2013. The steel scrap age. *Environ. Sci. Technol.* 47 (7), 3448–3454.
- Pearson, K., 1895. VII. Note on regression and inheritance in the case of two parents. *Proc. Roy. Soc. Lond.* 58 (347–352), 240–242.
- Rauch, J.N., 2009. Global mapping of Al, Cu, Fe, and Zn in-use stocks and in-ground resources. *Proc. Natl. Acad. Sci. U. S. A* 106 (45), 18920–18925.
- Rong, A., Lahdelma, R., 2008. Fuzzy chance constrained linear programming model for optimizing the scrap charge in steel production. *Eur. J. Oper. Res.* 186 (3), 953–964.
- Song, L., Zhang, C., Han, J., Chen, W.Q., 2019. In-use product and steel stocks sustaining the urbanization of Xiamen, China. *Ecosys. Health Sustain.* 5 (1), 110–123.
- Song, L., Wang, P., Hao, M., Dai, M., Xiang, K., Li, N., Chen, W.-Q., 2020. Mapping provincial steel stocks and flows in China: 1978–2050. *J. Clean. Prod.* 262, 121393.
- Sterner, T., Barbier, E.B., Bateman, I., van den Bijgaart, I., Crépin, A.-S., Edenhofer, O., Fischer, C., Habla, W., Hassler, J., Johansson-Stenman, O., et al., 2019. Policy design for the anthropocene. *Nat. Sustain.* 2 (1), 14–21.
- Tanikawa, H., Hashimoto, S., 2009. Urban stock over time: spatial material stock analysis using 4d-GIS. *Build. Res. Inf.* 37 (5–6), 483–502.
- Tian, S., Jiang, J., Zhang, Z., Manovic, V., 2018. Inherent potential of steelmaking to contribute to decarbonisation targets via industrial carbon capture and storage. *Nat. Commun.* 9 (1), 4422.
- United Nations, 2018. World urbanization prospects, the 2018 revision. In: United Nations, N.Y. (Ed.).
- Wang, T., Müller, D.B., Hashimoto, S., 2015. The Ferrous find: counting iron and steel stocks in China's economy. *J. Ind. Ecol.* 19 (5), 877–889.
- Wang, P., Li, W., Kara, S., 2017. Cradle-to-cradle modeling of the future steel flow in China. *Resour. Conserv. Recycl.* 117, 45–57.
- Weisz, H., Suh, S., Graedel, T.E., 2015. Industrial Ecology: the role of manufactured capital in sustainability. *Proc. Natl. Acad. Sci. U. S. A* 112 (20), 6260–6264.
- World Steel Association, 2019. World Steel in Figures. World Steel Association, Brussels, Belgium.
- Yu, B., Deng, S., Liu, G., Yang, C., Chen, Z., Hill, C.J., Wu, J., 2018. Nighttime light images reveal spatio-temporal dynamics of global anthropogenic resources accumulation above ground. *Environ. Sci. Technol.* 52 (20), 11520–11527.
- Zhang, C., Chen, W.-Q., Liu, G., Zhu, D.-J., 2017. Economic growth and the evolution of material cycles: an analytical framework integrating material flow and stock indicators. *Ecol. Econ.* 140, 265–274.
- Zhang, C., Chen, W.-Q., Ruth, M., 2018. Measuring material efficiency: a review of the historical evolution of indicators, methodologies and findings. *Resour. Conserv. Recycl.* 132, 79–92.
- Zhang, W., Cui, Y., Wang, J., Wang, C., Streets, D.G., 2020. How does urbanization affect CO₂ emissions of central heating systems in China? An assessment of natural gas transition policy based on nighttime light data. *J. Clean. Prod.* 276, 123188.
- Zhou, Y., Varquez, A.C., Kanda, M., 2019. High-resolution global urban growth projection based on multiple applications of the SLEUTH urban growth model. *Sci. data* 6 (1), 34.