

Article

Modeling In-Use Steel Stock in China's Buildings and Civil Engineering Infrastructure Using Time-Series of DMSP/OLS Nighttime Lights

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Received: 19 March 2014; in revised form: 16 May 2014 / Accepted: 19 May 2014 /

Published: 27 May 2014

Abstract: China's rapid urbanization has led to increasing steel consumption for buildings and civil engineering infrastructure. The in-use steel stock in the same is considered to be closely related to social welfare and urban metabolism. Traditional approaches for determining the in-use steel stock are labor-intensive and time-consuming processes and always hindered by the availability of statistical data. To address this issue, this study proposed the use of long-term nighttime lights as a proxy to effectively estimate in-use steel stock for buildings (IUS SB) and civil engineering infrastructure (IUS SCE) at the provincial level in China. Significant relationships between nighttime lights *versus* IUS SB and IUS SCE were observed for provincial variables in a single year, as well as for time series variables of a single province. However, these relationships were found to differ among provinces (referred to as “inter-individual differences”) and with time (referred to as “temporal differences”). Panel regression models were therefore proposed to estimate IUS SB and IUS SCE in consideration of the temporal and inter-individual differences based on a dataset covering 1992–2007. These models were validated using data for 2008, and the results showed good estimation for both IUS SB and IUS SCE. The proposed approach

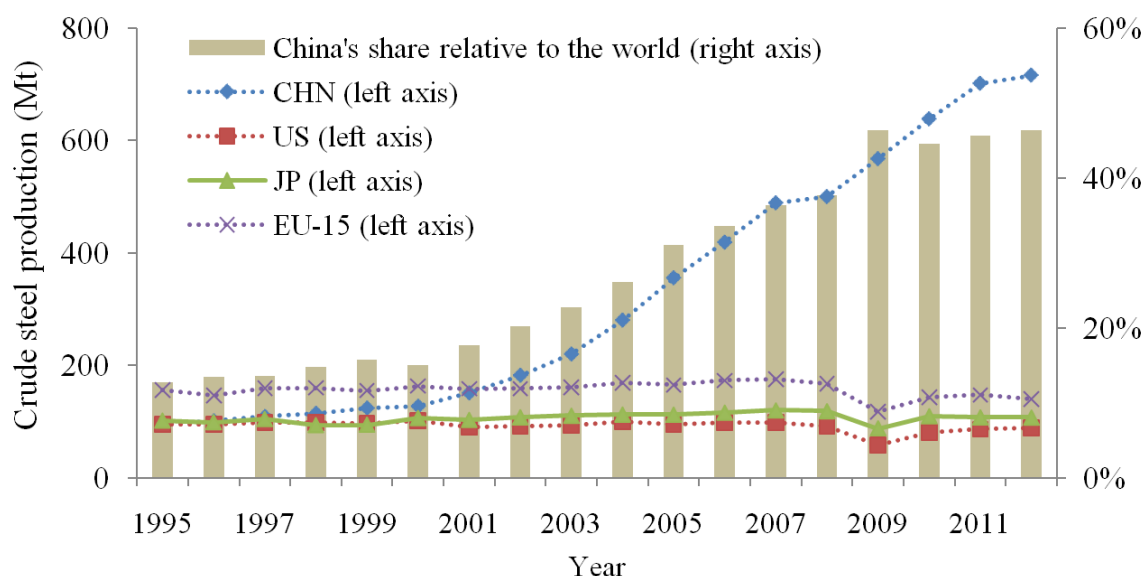
can be used to easily monitor the dynamic of IUSSB and IUSSCE in China. This should be critical in providing valuable information for policy making regarding regional development of buildings and infrastructure, sustainable urban resource management, and cross-boundary material recycling.

Keywords: in-use steel stock; DMSP/OLS nighttime lights; long-term; China; panel regression analysis

1. Introduction

Currently, China is undoubtedly experiencing a phase of rapid urbanization and civil infrastructure construction. Local and central governments are investing heavily in buildings and civil engineering infrastructure, such as highways and railways [1,2]. In this regard, the consumption of steel, the most widely used construction material, is rapidly increasing [3,4]. In 2012, China's crude steel production (Figure 1) and apparent steel consumption accounted for 46.3% and 45.7% of the world's total, respectively [5,6]. In particular, in 2013, steel consumption in the Chinese construction sector was projected to reach 56.6% of the total consumption [7]. It is also important to note that as one of the main emitters of CO₂, the iron/steel industry in China emitted 1.17 billion tons of CO₂ in 2009, which accounted for 50% of the total emission amount of the steel industry worldwide [8]. In this light, it is essential to realize sustainable resource management for steel from the viewpoint of achieving environmental protection and a low-carbon society in rapidly urbanizing China.

Figure 1. Crude steel production in China and the world. (Source: revised from [5] by the author).



Toward this end, an urgent issue requiring attention is the effective and efficient investigation of the steel stock in the society. A large amount (by weight) of steel is stocked in steel-containing products (e.g., buildings and civil engineering infrastructure) until their lifetime expires; this is usually referred

to as in-use steel stock [9,10]. Such stock is invaluable in terms of people's lives, social production, and economic development [11]. Furthermore, as an important component of urban metabolism, the size of in-use steel stock serves as an important measure of old scrap supply and recyclable steel [10]. Therefore, the reliable and real-time estimation of in-use steel stock could promote sustainable resource management and development of buildings and infrastructure in a transitional economy like China.

One of the traditional methods for the estimation of in-use steel stock is the top-down approach, in which the magnitude of in-use steel stock is calculated by contrasting the difference between steel inflow and outflow within a defined boundary [12]. The steel inflow (also referred to as "steel consumption") is calculated from time-series statistical data describing steel production and trade between nations or regions, whereas the steel outflow is determined by the lifetime of steel-containing products. Another method is the bottom-up approach, in which the in-use steel stock is calculated as the sum of the quantity of different steel-containing products multiplied by their average steel concentration [12]. Although both approaches provide a reasonable estimation of in-use steel stock, their applicability is always hindered by data availability. For the top-down approach, it is difficult to acquire in-use steel stock at a sub-national level owing to the lack of statistical data, whereas for the bottom-up approach, considerable labor costs are incurred to investigate the quantity and average steel concentration of steel-containing products.

Compared with the traditional approach, satellite estimation offers several advantages such as low cost, high spatial resolution and strong capacity for worldwide observations. Since 1992, global nighttime lights have been monitored by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS). Thus far, the DMSP/OLS sensor has produced two types of nighttime light images with a spatial resolution of 30 arc-seconds: (1) Global Radiance Calibrated Nighttime Lights which consists of light intensity with radiance-calibrated values that is publicly available only for several discontinuous years, and (2) DMSP-OLS Nighttime Lights Time Series (Version 4), which provides long-term (1992–2012) non-radiance-calibrated light intensity with digital number (DN) values between 0 and 63. Nighttime lights products have been proven to serve as a good proxy of several socioeconomic indicators such as human population [13], gross domestic product (GDP) and CO₂ emission [14], marketed economic activity [15] and electricity consumption [16]. Meanwhile, Rauch [17] proved that it is also possible to map in-use metals (aluminium, copper, iron, and zinc) stocks from nighttime lights based on the linear regression between GDP and both in-use stocks and nighttime lights.

Lights signals recorded by DMSP/OLS are mainly obtained from lit buildings and civil engineering infrastructure [18]. Usually, buildings and civil engineering infrastructure are considered as the main steel-containing products [19]. Therefore, some studies have explored the relationship between in-use steel stock and nighttime lights at the national and regional levels [19–23]. Taguchi *et al.* [21] proposed an empirical relationship between in-use steel stock and light intensity on a mesh-by-mesh basis for selected regions in Tokyo, Japan. Nighttime lights are also a good proxy of in-use steel stock at the prefecture level in Japan [19,21]. In China, Hsu *et al.* [24] estimated in-use steel stock at the provincial scale from nighttime lights using the national regression model established based on 41 sample countries. However, it should be noted that these models were proposed using the above-described Global Radiance Calibrated Nighttime Lights product in 2006; therefore, they may remain applicable for only a limited time owing to the limited availability of these products. This limitation makes it difficult to

construct long-term in-use steel stock from nighttime lights using present algorithms in China and, further, to study the in-use steel stock dynamics.

However, modeling the long-term variation of in-use steel stock from nighttime lights is actually more important for China because of its rapid urbanization and corresponding increase in steel consumption. In this study, we mainly focus on this issue. To model the long-term in-use steel stock from nighttime lights in China, potential factors influencing the relationship between in-use steel stock and nighttime lights need to be considered. According to Ma *et al.* [25], the relationships between nighttime lights and socioeconomic indicators (e.g., GDP, population, built-up area, electric power consumption) for a long-term dataset varied among regions (referred to as inter-individual differences in this study) owing to the vast regional disparity in socioeconomic indicators in China. Meanwhile, in other regions, the relationships between nighttime lights and the population, as well as GDP, were also reported to vary among regions [15,26,27]. For instance, to reduce the effects of regional disparity, Sutton and Costanza [15] classified the world's cities into three main groups according to the countries' GDP level and then estimated the cities' population from nighttime lights for each group.

In this study, we hypothesized that the relationship between in-use steel stock and nighttime lights is impacted by temporal and inter-individual differences. The objective is to provide an alternative, efficient approach for estimating long-term in-use steel stock of buildings (IUSSB) and civil engineering infrastructure (IUSSCE) in China at a provincial level from nighttime lights with consideration of temporal and inter-individual influences, so as to support sustainable resource management and circular economy strategy. Toward this end, the long-term (1992–2008) in-use steel stock and DMSP-OLS Nighttime Lights Time Series products were combined as a panel dataset. The temporal and inter-individual effects in the modeling long-term in-use steel stock from nighttime lights were then investigated using least squares (LS) regression analysis at cross-sectional and time-series dimensions. Panel regression analysis, which is widely used in studies of economy [28–30], as well as of urbanization and urban metabolism [31], was eventually adopted to derive the in-use steel stock from nighttime lights by controlling these temporal and inter-individual influences, and the performance of the panel regression model was validated.

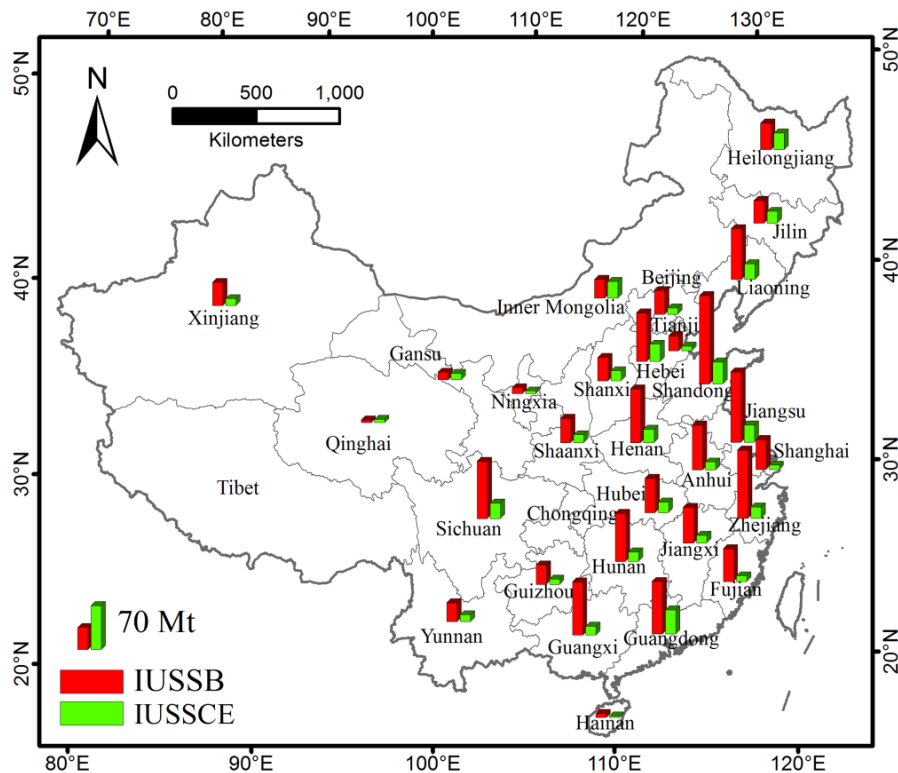
2. Data and Methodologies

2.1. Time-Series Dataset of Provincial In-Use Steel Stock in China

Time-series data of in-use steel stock (1978–2008) at the provincial level in China are provided by Han and Xiang [32] and Zheng *et al.* [33]. In brief, this dataset calculates steel stocked in buildings, roads, railways, and water pipes in mainland China from statistical data using the bottom-up approach. The in-use steel stock is classified as IUSSB and IUSSCE. IUSSCE includes steel stock of roads, railways, and water pipes. IUSSB in Han and Xiang [32] included steel stock of residential buildings in urban and rural areas, and it has been updated to include steel stock of both residential and commercial buildings by Han (personal communication). To match the nighttime lights data, we only adopted the data associated with 29 provinces in China from 1992 to 2008. The Tibet province is excluded in our following analysis owing to the lack of IUSSCE data. Moreover, as noted by Han and Xiang [32], Chongqing municipality is still considered as a part of Sichuan province for long-term

consistency (Figure 2). To preliminarily validate this dataset, we summed all the provincial IUSSB and compared them with those of Shi *et al.* [34], who calculated the in-use steel stock at the national level from statistics. These two datasets generally showed good consistency (see Supplementary materials).

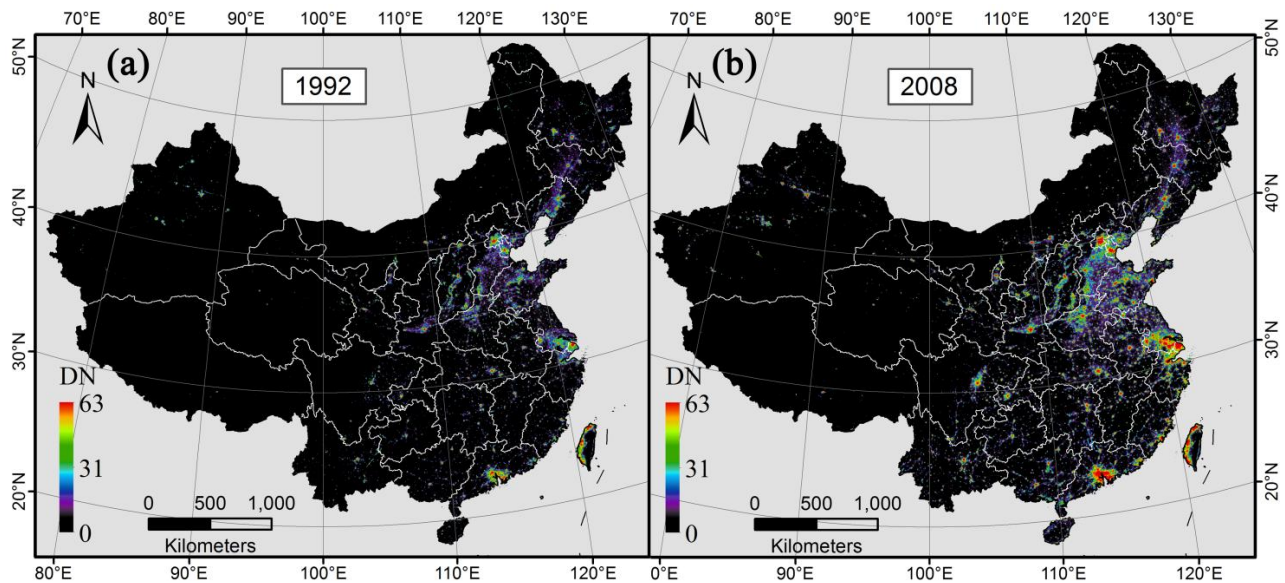
Figure 2. Distribution of provincial IUSSB and IUSSCE for mainland China in 2008.



2.2. Multi-Temporal Nighttime Light Dataset

Satellite images of DMSP-OLS Nighttime Lights Time Series (Version 4) covering the whole of China during 1992–2008 were obtained from the National Geophysical Data Center (NGDC) of NOAA (<http://ngdc.noaa.gov/eog/>). The annual composites of nighttime lights used in our study were derived from five individual satellites (F10, F12, F14, F15, and F16) with a DN of 0–63 and spatial resolution of 30 arc-seconds (~1 km) (Figure 3). Each satellite has a lifespan of 3–8 years, and therefore, there are instances in which two nighttime light imageries were observed by separate satellites in one particular year, such as in 1994 and during 1997–2007. Because there is no in-flight calibration for the DMSP/OLS sensor, the nighttime light imageries obtained by different satellites cannot be compared directly. To address this issue, we adopted Liu *et al.*'s [35] quadratic model to inter-calibrate all the annual nighttime light imageries using the imagery of F162007 for Jixi city in Heilongjiang Province. Furthermore, because the steel stock of gas-related infrastructure is not considered, Elvidge *et al.*'s [36] gas flare maps were used to remove the nighttime lights emitted by gas flares. From 1992 to 2008, a total of 29 inter-calibrated nighttime light imageries were produced by the abovementioned procedures. For individual imagery, DNs were aggregated according to the administrative boundaries of China's provinces. Ultimately, between the two nighttime lights imageries obtained by separate satellites for one year, the one showing a higher correlation with the in-use steel stock was selected to assemble the time-series dataset (see details in Section 3.1).

Figure 3. Spatial distribution of DMSP/OLS nighttime lights in China in (a) 1992 and (b) 2008.



2.3. Empirical Regression Model for In-Use Steel Stock at Provincial Level

China's provinces have different socioeconomic statuses and boundary scales. Normalization is widely used to reduce this type of inter-individual difference [19]. Therefore, we first normalized the total in-use steel stock and nighttime lights of a province by its administrative area, in order to investigate whether normalization can reduce the inter-individual difference. Early studies proved that the relationship between residential area and population can be described using a power function [37,38]. Based on this, the population was estimated from nighttime lights by assuming a power relationship between the two variables [15]. Meanwhile, the GDP was also suggested to vary with nighttime lights following a power function. Therefore, we assumed herein that the relationship between the normalized in-use steel stock and the nighttime lights also followed the power function

$$steelstock = \alpha \cdot (light)^\beta \quad (1)$$

and that function can be transformed to log-linear form as:

$$\log(steelstock) = k + \beta \cdot \log(light) \quad (2)$$

where *steelstock* and *light* are the normalized in-use steel stock and normalized nighttime lights, respectively, and α , k , and β are coefficients of the fitting model, where k equals $\log(\alpha)$. It should be noted that the coefficient β represents both the empirical slope of the log-linear regression and light elasticity of the in-use steel stock. In other words, β can be used as a measure of the strength and magnitude of the correlation between the growth of nighttime lights and the in-use steel stock.

In our study, nighttime lights and in-use steel stock (specific to IUSSB or IUSSCE) over 17 years (1992–2008) for 29 provinces in China were combined as one panel data, which contains two dimensions: time-series dimension and cross-sectional dimension. For each dimension, LS estimators were conducted between the nighttime lights *versus* IUSSB and IUSSCE based on Equation (2), and the log-linear correlation was evaluated by the determination coefficient (R^2) and root mean square error

(RMSE). The cross-sectional regression was used to analyze the linear relationship between provincial in-use steel stock and nighttime lights for a specific year, whereas the time-series regression focused on the linear relationship between the long-term in-use steel stock and the nighttime lights for a specific province.

To establish a uniform relationship between the long-term in-use steel stock and the nighttime lights, panel regression analysis was used. Normally, a panel regression model can be written as:

$$\log(\text{steelstock}_{i,t}) = k + \beta \cdot \log(\text{light}_{i,t}) + u_i + \varepsilon_{i,t} \quad (3)$$

where $\text{steelstock}_{i,t}$ and $\text{light}_{i,t}$ are the normalized in-use steel stock and nighttime lights for the i th province in the t th year, respectively. u_i is the between-entity error for the i th province and $\varepsilon_{i,t}$ represents the within-entity error. The regression error equals the sum of u_i and $\varepsilon_{i,t}$. Note that u_i (also referred to as “inter-individual differences”) is assumed to be independent of $\varepsilon_{i,t}$.

In our study, the time-fix effect is tested under a null hypothesis of joint test, which advocates that the coefficients of time dummies are equal to 0. According to the returned p -value (<0.05), we rejected the null hypothesis. This suggested that the effect of temporal variability should be considered. Therefore, a time dummy variable σ_t was added to the model to control the temporal effect (Equation (4)). A first-order autoregressive error term $\varepsilon_{i,t-1}$, which is a component of $\varepsilon_{i,t}$, was advocated in the linear model by statistical tests involving serial correlation and heteroskedasticity [39,40] (Equation (5)). Meanwhile, according to the variation characteristic of σ_t as shown in results later, we empirically hypothesized that σ_t follows a vapor pressure function over time. The final panel regression model in consideration of temporal and inter-individual differences is

$$\log(\text{steelstock}_{i,t}) = k + \beta \cdot \log(\text{light}_{i,t}) + \sigma_t + u_i + \varepsilon_{i,t} \quad (4)$$

$$\varepsilon_{i,t} = \rho \cdot \varepsilon_{i,t-1} + z_{i,t} \quad (5)$$

$$\sigma_t = \exp[c_0 + c_1/\Delta t + c_2 \cdot \ln(\Delta t)], \Delta t = t - t_0 + 1 \quad (6)$$

where $\varepsilon_{i,t-1}$ and ρ are the first-order autoregressive error term and its coefficient, respectively; $z_{i,t}$ is independent and identically distributed (i.i.d.); c_0 , c_1 , and c_2 are coefficients of the vapor pressure model; Δt denotes the gap of year; and t_0 indicates the start year. For instance, Δt for 1992 is 1, and that for 2008 is 17.

In the present study, panel data for 1992–2007 were included in the development of the panel regression model, and data for 2008 were used to validate the model performance. According to the Hausman specification test [41], a null hypothesis stating that the between-entity error u_i is not correlated with the independent variables of the model was tested. According to the p -value (>0.05), the null hypothesis is not rejected. Hereby, we adopted the feasible generalized least squares (FGLS) estimator and conducted our panel regression analysis using the “xtregar” command in Stata 12.0.

3. Results

3.1. Regression Analysis for Individual Year

Table 1 summarizes the cross-sectional regression results for IUSSB and IUSSCE based on 29 nighttime light imageries. In general, both R^2_{building} and R^2_{civil} were higher than 0.84 during the entire period, suggesting that nighttime lights had a strong correlation with IUSSB and IUSSCE. Furthermore, nighttime lights were a slightly better fit to IUSSCE than to IUSSB, showing higher

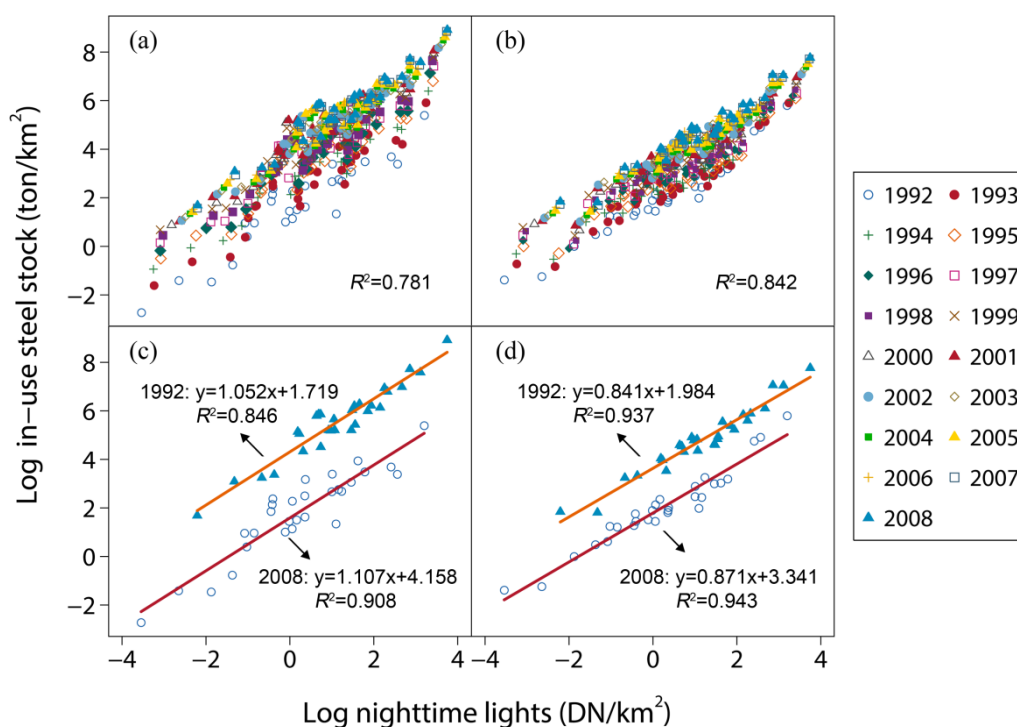
R^2_{civil} than $R^2_{building}$ for the same year. This is consistent with previous studies conducted in other regions [19,21,22]. In this study, we conducted regression between the nighttime lights and the in-use steel stock for the whole province. Thus, as suggested by Hsu *et al.* [21], one possible reason for higher R^2_{civil} than $R^2_{building}$ is the different distribution pattern between IUSSCE and IUSSB within a province in that IUSSB is distributed mainly in urban areas whereas IUSSCE is spread throughout the study area. To form a time-series dataset from 1992 to 2008, we selected the nighttime light imageries with a higher R^2_{ave} (see the last column of Table 1), which was given by the average of R^2_{civil} and $R^2_{building}$. For example, R^2_{ave} of F101994 nighttime lights (0.904) was higher than that of F121994 (0.897); therefore, F101994 nighttime light imagery was chosen for further analysis.

Table 1. Cross-sectional regression results for in-use steel stock for buildings (IUSSB) and civil engineering infrastructure (IUSSCE) based on five individual satellites. The years and averages (R^2_{avg}) of $R^2_{building}$ and R^2_{civil} with underlines indicate 17 imageries (out of 29) that were selected to form the time-series data.

Satellite	Year	IUSSB				IUSSCE				R^2_{avg}
		$\beta_{building}$	$k_{building}$	$R^2_{building}$	$RMSE$	β_{civil}	k_{civil}	R^2_{civil}	$RMSE$	
F10	<u>1992</u>	1.052	1.719	0.846	0.713	0.841	1.984	0.937	0.347	<u>0.892</u>
F10	<u>1993</u>	1.024	2.265	0.884	0.575	0.801	2.146	0.927	0.349	<u>0.906</u>
F10	<u>1994</u>	1.003	2.687	0.891	0.541	0.768	2.331	0.916	0.359	<u>0.904</u>
F12	1994	0.988	2.728	0.893	0.538	0.749	2.365	0.901	0.389	0.897
F12	<u>1995</u>	0.988	2.950	0.891	0.536	0.745	2.469	0.911	0.360	<u>0.901</u>
F12	<u>1996</u>	0.997	3.166	0.888	0.541	0.741	2.610	0.907	0.362	<u>0.898</u>
F12	<u>1997</u>	1.003	3.317	0.885	0.547	0.742	2.721	0.906	0.362	<u>0.896</u>
F12	1998	1.038	3.502	0.898	0.525	0.77	2.817	0.910	0.355	0.904
F12	1999	1.020	3.825	0.908	0.512	0.746	3.042	0.898	0.365	0.903
F14	1997	1.009	3.362	0.884	0.549	0.739	2.758	0.888	0.396	0.886
F14	<u>1998</u>	1.010	3.480	0.903	0.518	0.75	2.800	0.908	0.352	<u>0.906</u>
F14	<u>1999</u>	1.014	3.658	0.904	0.520	0.755	2.911	0.909	0.358	<u>0.907</u>
F14	2000	1.051	3.758	0.879	0.595	0.788	2.969	0.909	0.356	0.894
F14	2001	1.041	3.949	0.890	0.537	0.802	3.107	0.931	0.323	0.911
F14	2002	1.058	4.009	0.915	0.451	0.801	3.172	0.923	0.324	0.919
F14	2003	1.064	4.040	0.924	0.425	0.817	3.201	0.927	0.319	0.926
F15	<u>2000</u>	1.018	3.783	0.886	0.530	0.764	2.988	0.916	0.336	<u>0.901</u>
F15	<u>2001</u>	1.016	3.914	0.895	0.523	0.78	3.082	0.927	0.306	<u>0.911</u>
F15	<u>2002</u>	1.031	3.982	0.913	0.446	0.791	3.143	0.930	0.302	<u>0.922</u>
F15	<u>2003</u>	1.046	4.019	0.925	0.421	0.813	3.176	0.931	0.307	<u>0.928</u>
F15	2004	1.061	4.064	0.907	0.513	0.825	3.206	0.939	0.291	0.923
F15	2005	1.091	4.167	0.905	0.517	0.856	3.297	0.952	0.274	0.929
F15	2006	1.101	4.181	0.915	0.458	0.866	3.331	0.943	0.286	0.929
F15	2007	1.117	4.182	0.928	0.453	0.871	3.358	0.952	0.278	0.940
F16	<u>2004</u>	1.098	3.963	0.911	0.476	0.854	3.128	0.943	0.283	<u>0.927</u>
F16	<u>2005</u>	1.071	4.111	0.911	0.477	0.835	3.259	0.951	0.259	<u>0.931</u>
F16	<u>2006</u>	1.078	4.147	0.917	0.442	0.849	3.303	0.945	0.279	<u>0.931</u>
F16	<u>2007</u>	1.095	4.157	0.932	0.413	0.857	3.335	0.950	0.269	<u>0.941</u>
F16	<u>2008</u>	1.107	4.158	0.908	0.462	0.871	3.341	0.943	0.280	<u>0.926</u>

During the entire period, the slopes ($\beta_{building}$ and β_{civil}) of the linear functions between nighttime lights *versus* IUSSB and IUSSCE showed relatively narrow ranges whereas the intercepts ($k_{building}$ and k_{civil}) showed a large difference. Figure 4 shows clearer evidence of the same. Taking IUSSB as an example, Figure 4a shows a plot of the entire provincial IUSSB against the corresponding nighttime lights from 1992 to 2008. Figure 4c shows a plot of a simplified scatter diagram with special emphasis on samples at the start (1992) and end (2008) years. These two figures show that the amount of steel stock follows a similar increasing trend with nighttime lights in 1992 and 2008, whereas there was an obvious gap between the intercepts of 1992 and 2008. IUSSCE exhibited similar trends, as shown in Figure 4b,d. As expected, these findings indicate that it is necessary to consider the temporal effect in the modeling of long-term IUSSB and IUSSCE from nighttime lights.

Figure 4. Scatter plots for provincial variables over the entire period: (a) nighttime lights *versus* IUSSB; (b) nighttime lights *versus* IUSSCE. Scatter plots with linear regression lines for variables in 1992 and 2008: (c) nighttime lights *versus* IUSSB; (d) nighttime lights *versus* IUSSCE. Solid lines in black, orange, and red are linear regression lines.



3.2. Regression Analysis for Individual Province

For each province, time-series regressions between nighttime lights *versus* IUSSB and IUSSCE were performed and the results are summarized in Table 2. In general, both $R^2_{building}$ and R^2_{civil} were larger than 0.87, and their average, R^2_{avg} , was 0.899–0.984. These results indicated that nighttime lights were also a good proxy of IUSSB and IUSSCE for all provinces over a long time scale. Nighttime lights in Beijing municipality showed the highest correlation with in-use steel stock and those in Jiangxi province, the lowest. More importantly, it is observed that both the slopes ($\beta_{building}$ and β_{civil}) and the intercepts ($k_{building}$ and k_{civil}) showed wide variations across provinces. These findings indicated

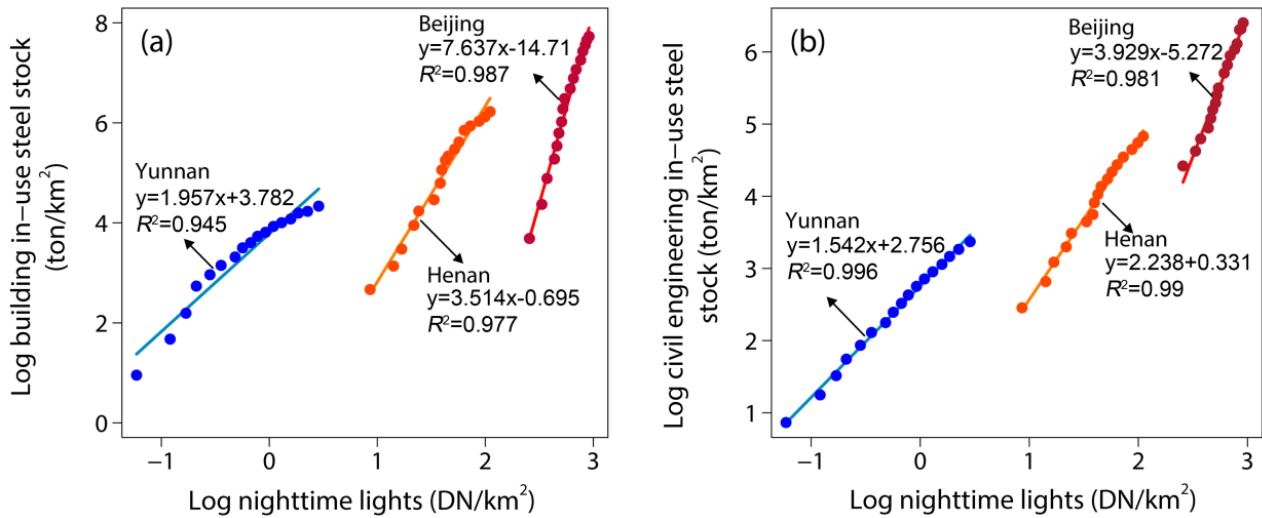
that the simple normalization of the provincial in-use steel stock and nighttime lights by the administrative area cannot reduce the inter-provincial effects effectively, and the other method is necessarily required.

Figure 5 shows a graphical representation of the relationships between long-term nighttime lights *versus* IUSSB and IUSSCE in exemplar provinces—Beijing, Henan, and Yunnan that belong to the eastern, middle, and western regions of China, respectively. Figure 5a,b shows that the regression functions for these three provinces differed considerably from each other. The regression lines for Beijing were excessively steep, whereas those for Henan and Yunnan were gentler. One possible factor causing these differences was the growth rate of in-use steel stock with the increase in nighttime lights, and another factor may be related to the saturated lighting signals in the urban core [42], as discussed later. These findings imply that the time-series regressions established for one province by LS regression are not applicable to other provinces owing to the existence of the inter-individual effect.

Table 2. Time-series regression results for IUSSB and IUSSCE. R^2_{avg} represents the average of $R^2_{building}$ and R^2_{civil} .

Province	IUSSB				IUSSCE				R^2_{avg}
	$\beta_{building}$	$k_{building}$	$R^2_{building}$	$RMSE$	β_{civil}	k_{civil}	R^2_{civil}	$RMSE$	
Anhui	2.345	2.720	0.972	0.165	1.784	1.790	0.989	0.079	0.981
Beijing	7.637	−14.71	0.987	0.143	3.929	−5.272	0.981	0.088	0.984
Fujian	2.872	1.961	0.966	0.192	2.091	1.108	0.976	0.115	0.971
Gansu	3.035	4.662	0.914	0.349	1.913	3.954	0.947	0.169	0.931
Guangdong	4.061	−2.574	0.956	0.201	3.467	−2.456	0.958	0.169	0.957
Guangxi	2.737	4.033	0.964	0.219	1.945	2.769	0.981	0.111	0.973
Guizhou	2.646	4.349	0.979	0.190	1.502	3.380	0.972	0.125	0.976
Hainan	1.917	2.382	0.978	0.128	1.499	1.875	0.951	0.150	0.965
Hebei	4.323	−2.519	0.955	0.206	3.409	−1.771	0.963	0.148	0.959
Heilongjiang	3.184	2.380	0.928	0.291	2.128	2.597	0.924	0.199	0.926
Henan	3.514	−0.695	0.977	0.172	2.238	0.331	0.990	0.071	0.984
Hubei	3.662	1.925	0.950	0.280	1.966	2.320	0.990	0.066	0.970
Hunan	2.625	4.198	0.931	0.318	1.606	3.090	0.970	0.125	0.951
Inner Mongolia	3.181	5.592	0.903	0.427	1.900	4.510	0.900	0.259	0.902
Jiangsu	3.489	−2.248	0.952	0.241	2.706	−1.813	0.965	0.159	0.959
Jiangxi	2.191	4.528	0.873	0.396	1.687	3.124	0.925	0.228	0.899
Jilin	3.369	2.146	0.892	0.338	2.620	2.108	0.946	0.180	0.919
Liaoning	5.083	−2.695	0.969	0.183	2.973	−0.141	0.971	0.104	0.970
Ningxia	3.034	2.116	0.969	0.187	2.407	2.028	0.960	0.168	0.965
Qinghai	2.494	7.396	0.871	0.463	1.611	5.464	0.934	0.206	0.903
Shaanxi	3.133	2.063	0.888	0.413	2.046	1.814	0.976	0.118	0.932
Shandong	3.142	−0.701	0.932	0.225	2.935	−1.842	0.967	0.143	0.950
Shanghai	5.705	−12.520	0.953	0.234	3.179	−5.081	0.957	0.125	0.955
Shanxi	5.015	−3.662	0.988	0.124	3.412	−1.624	0.979	0.112	0.984
Sichuan	2.756	4.390	0.955	0.306	1.422	3.264	0.992	0.064	0.974
Tianjin	6.806	−13.840	0.975	0.192	3.262	−3.968	0.973	0.095	0.974
Xinjiang	2.836	6.744	0.970	0.234	1.743	4.054	0.984	0.103	0.977
Yunnan	1.957	3.782	0.945	0.232	1.542	2.756	0.996	0.047	0.971
Zhejiang	2.476	1.464	0.942	0.256	1.867	0.698	0.968	0.141	0.955

Figure 5. Scatter plots for time-series variables in Beijing, Henan, and Yunnan: (a) nighttime lights *versus* IUSSB; (b) nighttime lights *versus* IUSSCE. Solid lines in blue, orange, and red are regression lines.



3.3. Development of In-Use Steel Stock Estimation Model

The results in Sections 3.1 and 3.2 confirmed our expectation that only one simple LS regression model was not suitable to model in-use steel stock over the whole of China from nighttime lights for a long-term scale owing to the influences of temporal and inter-provincial differences. Here, we used panel regression analysis to reduce the temporal and inter-provincial effects and to improve the performance of estimating in-use steel stock from nighttime lights. We first present the simple LS models based on the whole dataset (1992–2007) of nighttime lights and in-use steel stock for the purpose of comparison.

For IUSSB, the LS model was:

$$\log(IUSSB) = 3.396 + 1.133 \cdot \log(light) \quad (R^2 = 0.778, RMSE = 0.877) \quad (7)$$

For IUSSCE, the LS model was:

$$\log(IUSSCE) = 2.803 + 0.852 \cdot \log(light) \quad (R^2 = 0.843, RMSE = 0.534) \quad (8)$$

The panel regression models showed good fitting results (Table 3) with adjusted R^2 of 0.900 and 0.914 and corresponding $RMSE$ of 0.558 and 0.374 for IUSSB and IUSSCE, respectively. The detailed panel regression models for IUSSB and IUSSCE were:

$$\log(IUSSB_{i,t}) = 1.737 + 0.868 \cdot \log(light_{i,t}) + \sigma_t^{building} + u_i^{building} \quad (R^2 = 0.900, RMSE = 0.558) \quad (9)$$

$$\log(IUSSCE_{i,t}) = 2.001 + 0.656 \cdot \log(light_{i,t}) + \sigma_t^{civil} + u_i^{civil} \quad (R^2 = 0.914, RMSE = 0.374) \quad (10)$$

As shown in Table 3, nighttime lights showed significant positive correlations ($p < 0.001$) with IUSSB and IUSSCE. For every 1% increase in nighttime lights, the model predicted a 0.868% and 0.656% increase in IUSSB and IUSSCE, respectively. Details about $\sigma_t^{building}$, $u_i^{building}$, σ_t^{civil} , and u_i^{civil} , which are important components in the panel regression model, are described below.

Table 3. Statistics of the panel regression analysis for IUSSB and IUSSCE from 1992 to 2007. $N(obs.)$ and $N(group)$ denote the number of observations and groups, respectively; $\rho(ar)$ is the coefficient of the first-order autoregressive error term $\varepsilon_{i,t-1}$; $\sigma(e)$ and $\sigma(u)$ are the standard deviation of $z_{i,t}$ and u_i , respectively; and $\rho(fov)$ denotes the u_i fraction of the total variance. The asterisks (***) indicate the significance level (p) of 0.001.

	β	k	N (obs.)	N (group)	R^2 (adjusted)	RMSE	$\rho(ar)$	$\sigma(e)$	$\sigma(u)$	$\rho(fov)$
IUSSB	0.868 ***	1.737 ***	464	29	0.900	0.558	0.856	0.098	0.473	0.959
IUSSCE	0.656 ***	2.001 ***	464	29	0.914	0.374	0.880	0.053	0.279	0.959

The coefficients $\sigma_t^{building}$ and σ_t^{civil} represent the time-fixed effects in the panel regressions, which are independent of the inter-provincial differences. Figure 6 shows that $\sigma_t^{building}$ and σ_t^{civil} increase with a prolonged timeline following vapor pressure functions. Here, we selected vapor pressure functions because the increase rate of $\sigma_t^{building}$ and σ_t^{civil} both decreased with time. To describe this type of relationship, the vapor pressure function or logarithmic function is a good choice. Compared with the logarithmic function, the vapor pressure function showed better fitting results in our dataset. Table 4 lists the coefficients of the vapor pressure fitting models for $\sigma_t^{building}$ and σ_t^{civil} . These coefficients (*i.e.*, c_0 , c_1 , and c_2) were statistically significant ($p < 0.001$), and both models showed a strong prediction ability with R^2 of 1.000 and 1.000 and RMSE of 0.044 and 0.014 for $\sigma_t^{building}$ and σ_t^{civil} , respectively. The vapor pressure fit models for $\sigma_t^{building}$ and σ_t^{civil} are:

$$\sigma_t^{building} = \exp[0.767 - 2.976/\Delta t + 0.15 \cdot \ln(\Delta t)] \quad (11)$$

$$\sigma_t^{civil} = \exp[-5.06 - 2.949/\Delta t + 0.414 \cdot \ln(\Delta t)] \quad (12)$$

Figure 6. The time dummy variables σ_t are plotted against timeline Δt for (a) IUSSB and (b) IUSSCE. Solid lines in red are regression lines of the vapor pressure fitting models.

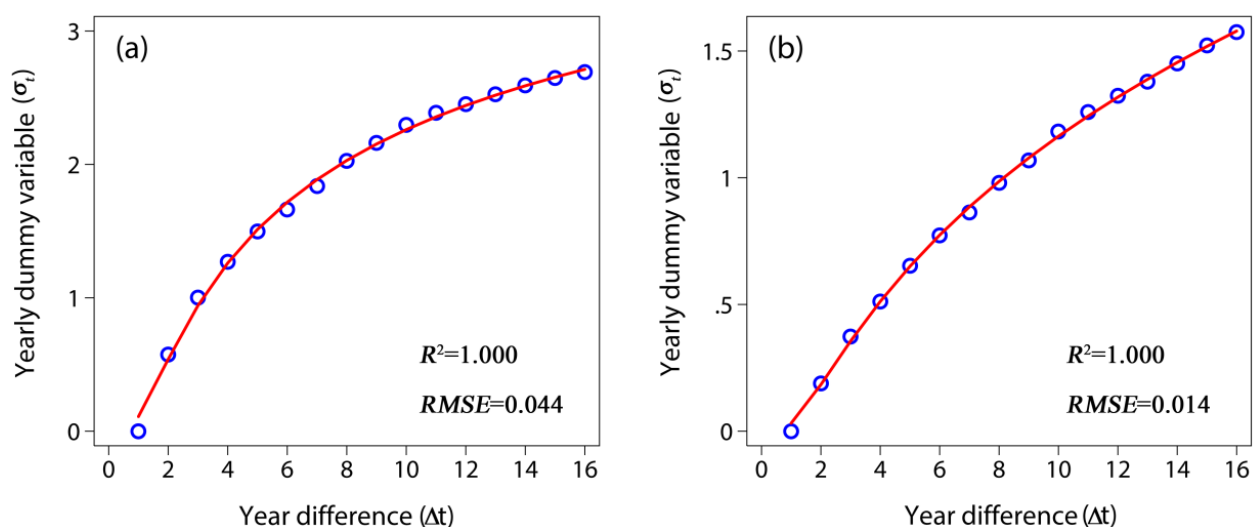


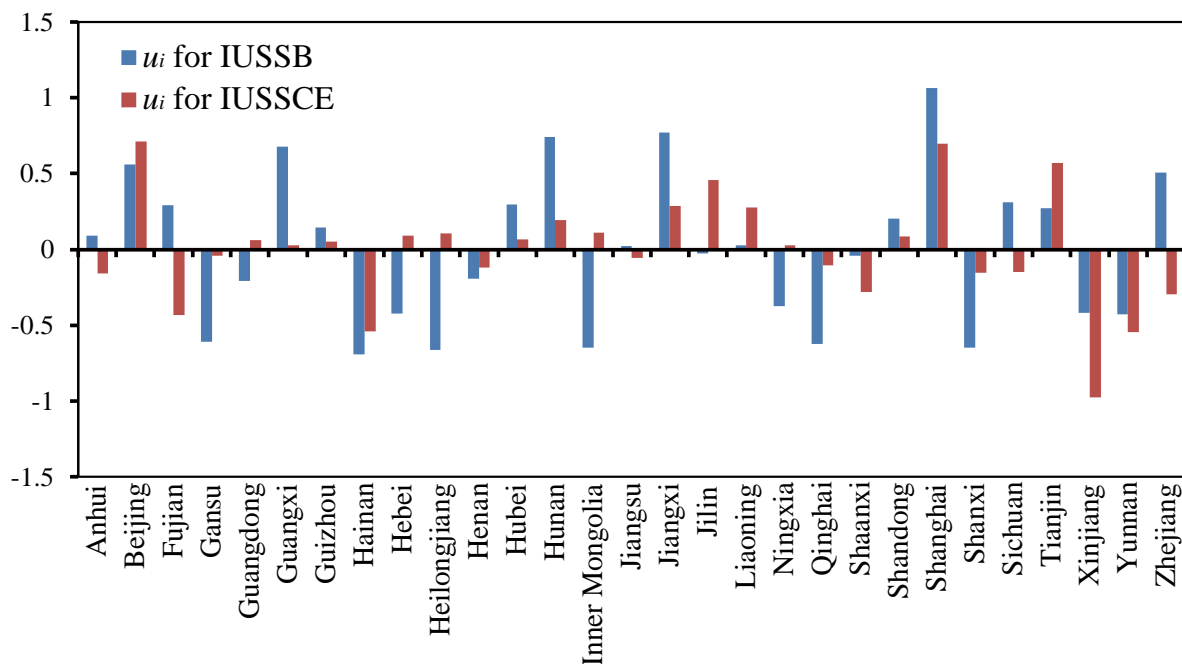
Figure 7 shows the components $u_i^{building}$ and u_i^{civil} for each province, and the detailed values are listed in the Appendix. $u_i^{building}$ and u_i^{civil} are used to reduce the inter-provincial differences in the panel regression. For instance, u_i is higher in Beijing and Shanghai than in the other provinces, suggesting

that if a uniform LS model is used without consideration of their inter-provincial differences, the in-use steel stocks in Beijing and Shanghai will be underestimated. Conversely, the relatively low u_i in Xinjiang, Hainan, and Yunnan indicated that the in-use steel stock will be overestimated using a uniform LS model. By adding u_i for each province in the panel regression model, the overestimation and underestimation of the LS model can be effectively compensated.

Table 4. Coefficients of vapor pressure fitting models for time dummy variables σ_t . The number of asterisks (*) indicate different significance levels (p): 1 = $p < 0.05$, 2 = $p < 0.01$, 3 = $p < 0.001$.

Models	IUSSB					IUSSCE				
	c_0	c_1	c_2	R^2	$RMSE$	c_0	c_1	c_2	R^2	$RMSE$
	0.767 ***	−2.976 ***	0.150 **	1.000	0.044	−0.506 ***	−2.949 ***	0.414 ***	1.000	0.014

Figure 7. Random-error component u_i for each province in panel regression model.

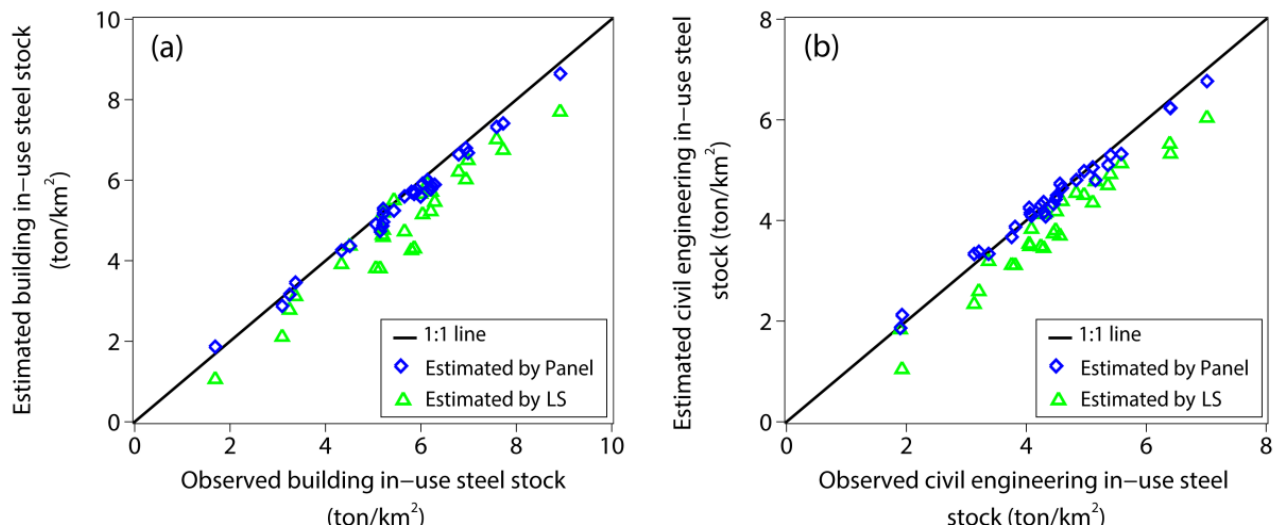


3.4. Model Validation

To validate the model performance, we applied the panel regression models and LS models for 2008 to derive IUSSB and IUSSCE from nighttime lights. Based on the vapor pressure fit models shown in Equations (11) and (12), the coefficients $\sigma_t^{building}$ and σ_t^{civil} in 2008 were projected to be 2.768 and 1.636, respectively. Figure 8 shows scatter plots between the estimated *versus* the observed IUSSB and IUSSCE for 29 provinces. Although the estimated values of the LS models were linearly correlated with statistical data for both IUSSB and IUSSCE with R^2 of 0.908 and 0.943, respectively, both IUSSB and IUSSCE were clearly underestimated by the LS models with $RMSE$ of 0.855 and 0.624, respectively. This is probably because the temporal and inter-provincial effects on the relationship between in-use steel stock and nighttime lights were neglected. The panel regression models showed good estimations for both IUSSB and IUSSCE; all the data were around the 1:1 lines

with R^2 of 0.992 and 0.987 and $RMSE$ of 0.238 and 0.154, respectively. These results indicate that the panel regression models are time-robust in deriving IUSSB and IUSSCE from nighttime lights at a nationwide scale in China.

Figure 8. Comparisons between estimated IUSSB (a) and IUSSCE (b) by the panel regression models and LS models *versus* observed IUSSB and IUSSCE in 2008.



4. Discussion

The steel stock in existing buildings and infrastructure is closely related to social production, urban metabolism, and resource conservation [10,11,43]. As with previous studies [19–22], we confirmed that time-series nighttime light imageries show good performance for estimating the in-use steel stock. Unlike the previous studies in which the estimation models were usually developed based on data for a specific year, this study proposed an approach to construct long-term IUSSB and IUSSCE from DMSP-OLS Nighttime Lights Time Series (Version 4) at the provincial level in China. We found that in China, which is a fast developing country, there were obvious temporal and inter-individual differences in the relationship between nighttime lights and in-use steel stock (Figures 3 and 4), even though we performed the preliminary normalization of these variables by the corresponding administrative area, which is a widely used method to reduce inter-individual differences. These findings were generally in agreement with those of Ma *et al.* [25], who observed that the quantitative responses of nighttime lights to changes in socioeconomic indicators followed different trends for individual cities. These results suggested that more attention should be given when applying a sole LS model to derive the long-term steel stock. Figure 8 showed that without consideration of the temporal and inter-individual effects, the in-use steel stock was clearly underestimated by LS models in 2008. To compensate for the temporal and inter-individual effects, panel regression analysis has been suggested as a useful technique by economists [28–30,44]. In this study, we first adopted panel regression analysis to model the long-term in-use steel stock, and its good performance showed that panel analysis is also a powerful tool for modeling the long-term in-use steel stock from nighttime lights.

The temporal effects in the relationship between nighttime lights and in-use steel stock may be related to the detection ability of the DMSP/OLS sensor. It is well known that this sensor can only

detect light signals with radiance exceeding $10^{-1} \text{ W}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}\cdot\mu\text{m}^{-1}$ [42,45]. However, steel was stocked in unlit buildings and infrastructure as well, such as underground parts [46]. Furthermore, a considerable amount of steel is stocked in buildings and infrastructure in sparsely populated areas where the nighttime light intensity is quite weak [47–49]. Such steel should also be considered a part of the unlit in-use steel stock. Theoretically, nighttime lights increase with lit in-use steel following a linear trend in log-log space (Figure 3), and the intercept of the linear function can be attributed to the unlit in-use steel stock. With the rapid urbanization in China, in-use steel stocks in both lit and unlit buildings and infrastructure are increasing along the timeline [3,9]. The increase in unlit in-use steel stock may increase the intercept of the cross-sectional LS models during 1992–2008 and gradually result in a large shift between the intercepts in 1992 and 2008, as shown in Figure 4. Inter-individual differences may be attributable to disparity in development across provinces, such as economic growth [50], population density [51], material/energy consumption [52], urban structure [53], and infrastructure investment [54]. These disparities may result in different proportions of lit and unlit buildings and infrastructure, which eventually caused diverse relationships between nighttime lights and in-use steel stock across provinces. Another factor may be the saturation problem of nighttime lights, which is a known challenge in the applications of DMSP/OLS data [42,55,56]. For instance, in Beijing, the ratio of saturated pixels was larger than that in Henan and Yunnan, which was one of the possible factors causing the sharper regression line for Beijing (Figure 5). Here, we need to state that the factors mentioned above are possible factors causing temporal and individual differences in the relationship between in-use steel stock and nighttime lights in China, and further investigations are still required to re-establish this proposition.

Although in-use steel stock can be calculated using statistical data, it is usually a labor-intensive and time-consuming process. Compared with statistical methods, our approach is a fast and easy operation process to model the long-term in-use steel stock at a provincial level from nighttime lights. In turn, this should help identify the discrepancies in the development of buildings and infrastructure across different regions of China and provide effective guidelines for investment for buildings and infrastructure [32]. Furthermore, real-time information about the provincial in-use steel stock should facilitate the analysis of the relationship between infrastructure services and economic growth [57–60]. Long-term modeling of the in-use steel stock could help promote efficient use of materials and provide reliable estimates for recyclable steel in the future [10,61–63]. Moreover, our study not only established panel regression models for the in-use steel stock that are suitable for all provinces in different years but also provided optional LS models that can be used to estimate the provincial in-use steel stock in a specific year or in-use steel stock dynamic for a specific province (Tables 1 and 2).

Although our model provides a good estimation of long-term in-use steel stock from nighttime lights in China, it may be inappropriate to apply our model directly at the county level or to other countries. This is because our model aimed to consider the temporal and inter-individual differences at provincial level in China, whereas these differences at the county level or in other countries may have different characteristics. However, we believe that our approach can be adapted at the county level and to other countries according to the local conditions. In addition, our model is based on the empirical relationship between nighttime lights and statistic-based in-use steel stock, which implies that the model parameters may depend on the training dataset. In future studies, we suggest compiling detailed ground dataset (e.g., 3D GIS dataset) because it can not only validate the performance of empirical

models proposed based on statistical data but also help to investigate the physical relationship between in-use steel stock and nighttime lights.

5. Conclusions

In this study, modeling of provincial in-use steel stock of buildings (IUSSB) and civil engineering infrastructure (IUSSCE) in China using the Defense Meteorological Satellite Program's Operational Linescan System (DMSP/OLS) Nighttime Light Time Series (Version 4) products was investigated based on a long-term dataset (1992–2008). We found that the log-linear relationship between in-use steel stock and nighttime lights varied with time, showing slope ranges of 0.988–1.117 and 0.739–0.831, and intercept ranges of 1.719–4.182 and 1.984–3.358 for IUSSB and IUSSE, respectively. Meanwhile, the log-linear relationship also showed provincial differences with slope ranges of 1.917–7.637 and 1.422–3.929, and intercept ranges of -14.71 – 7.396 and -5.272 – 5.464 for IUSSB and IUSSE, respectively. These findings indicate that it is not appropriate to use a sole least square (LS) regression model for estimation of long-term in-use steel stock in China.

To compensate for the temporal and individual differences, panel regression analysis was first used in this study to build estimation models of IUSSB and IUSSCE. The validation of model performance in 2008 showed obvious improvement of the panel regression model compared with the sole LS model, with decreases in root mean square error from 0.855 to 0.238 and from 0.624 to 0.154 for estimation of IUSSB and IUSSCE, respectively. These results suggested that the panel regression models are time-robust and suitable for the provincial levels of China. The fast and effective estimation of long-term steel accumulation from nighttime lights at a nationwide scale in China can further serve as a sound basis for understanding the disparity in the development of buildings and infrastructure as well as implementing cross-boundary material recycling in the future. The application of our approach needs be investigated at county level and in other countries in a future study.

Acknowledgments

The authors acknowledge the support of J. Han and L. Zheng for providing the dataset of provincial in-use steel stock based on statistical data in China, and the NOAA National Geographical Data Center for processing the DMSP-OLS Nighttime Lights Time Series (Version 4). We would also like to thank F. Shi for providing the in-use steel stock of China at the country level. Thanks are also due to the anonymous reviewers whose constructive suggestions helped to improve the clarity of this paper. This research was financially supported by the Environment Research and Technology Development Fund (1-1402) of the Ministry of the Environment, Japan, and Grants-in-Aid for Scientific Research A (25241027) and B (26281056).

Author Contributions

Hanwei Liang collected and processed the long-term nighttime lights data, performed the regression analysis, results interpretation, manuscript writing, and coordinated the revision activities. Hiroki Tanikawa and Yasunari Matsuno outlined the research topic and assisted with developing the

research design, and results interpretation. Liang Dong assisted with refining the research design, interpretation of results and manuscript revision.

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix

Table A1 shows the detailed values of the random-error components $u_i^{building}$ and u_i^{civil} , which represent the between-entity regression errors for the i th province in the panel regression models for estimating in-use steel stock of buildings (IUSSB) and civil engineering infrastructure (IUSSCE), respectively. By adding $u_i^{building}$ and u_i^{civil} for each province, the inter-provincial differences are effectively reduced in the panel regression models.

Table A1. The random-error components $u_i^{building}$ and u_i^{civil} for each province.

Province	$u_i^{building}$	u_i^{civil}
Anhui	0.092	−0.156
Beijing	0.561	0.712
Fujian	0.289	−0.433
Gansu	−0.609	−0.040
Guangdong	−0.210	0.063
Guangxi	0.678	0.029
Guizhou	0.143	0.054
Hainan	−0.693	−0.539
Hebei	−0.421	0.091
Heilongjiang	−0.661	0.106

Table 1. Cont.

Province	$u_i^{building}$	u_i^{civil}
Henan	−0.192	−0.117
Hubei	0.298	0.068
Hunan	0.744	0.197
Inner Mongolia	−0.649	0.110
Jiangsu	0.023	−0.054
Jiangxi	0.771	0.286
Jilin	−0.027	0.459
Liaoning	0.026	0.279
Ningxia	−0.371	0.027
Qinghai	−0.623	−0.105
Shaanxi	−0.041	−0.281
Shandong	0.205	0.090
Shanghai	1.067	0.698
Shanxi	−0.647	−0.154
Sichuan	0.309	−0.149
Tianjin	0.270	0.573
Xinjiang	−0.415	−0.973
Yunnan	−0.427	−0.543
Zhejiang	0.508	−0.297