Environmental Impact Assessment Review 93 (2022) 106731

Contents lists available at ScienceDirect

Environmental Impact Assessment Review

journal homepage: www.elsevier.com/locate/eiar

Exploring the effect of urban sprawl on carbon dioxide emissions: An urban sprawl model analysis from remotely sensed nighttime light data

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ARTICLE INFO

Keywords:
Nighttime light data
Urban sprawl
Carbon dioxide emissions
Southwest China

ABSTRACT

The easily and effectively exploration of *the effect of urban sprawl on carbon dioxide emissions* (EUC) is highly important for developing a sustainable urban spatial structure and a low-carbon urban planning system in a country. However, the comprehensive understanding of EUC and its transmission factors remain inadequate because previous studies were mainly concentrated on a single city, stage, and region based on the statistical data and traditional optical remotely sensed images. Thus, taking 41 typical cities in Southwest China as examples, an *urban sprawl* (US) model was developed for quantifying US from remotely sensed nighttime light data. The degree of EUC were then verified in different city sizes, stages, and regions. The transmission factors of EUC were further evaluated. Results show that US can aggravate *carbon dioxide emissions* (CE), and the robust analysis further confirms the positive effect of US on CE. US in small cities has the strongest effect on CE, whereas that in medium cities has the weakest effect. In addition, EUC is greater in pre-stage (2000–2009) than that in post-stage (2010–2018). EUC in Guizhou, Yunnan, and Sichuan–Chongqing gradually decreases. The transmission factor results indicate that US can aggravate CE through the urban transport, construction industry, and urban heat island. It is suggested that more attention should be paid to US environmental problems with China's future urban development.

1. Introduction

Since the industrial revolution, human activities have produced vast *greenhouse gas* (GHG) emissions, thereby increasing the imbalance of the GHG concentration and inducing climate change (Al-Ghussain, 2019). As a common challenge faced by the international community, climate change can produce many adverse effects, such as glacier melting, flooding, sea-level rise, economic crises, civil wars, and violence (Laufkötter et al., 2020; Miles-Novelo and Anderson, 2019). It was reported that global GHG emissions increased by approximately 15 billion tons in 1990–2014, and *carbon dioxide emissions* (CE) accounted for the main increase in GHG emissions (Zhang et al., 2021). In an effort to curb the economic, ecological and human well-being damage caused by climate change, 195 countries ratified the 2°C target of the Paris Agreement in 2018 (Mulder et al., 2021). Thus, reducing CE has become a worldwide focus to reply the climate change challenge. Meanwhile, as a major carbon emitter, China pledged to peak CE around 2030 and to strive to reach the peak as soon as possible (Yang et al., 2020).

As the center of socioeconomic activities, urban areas emitted 71% of global CE, which was expected to increase to 76% by 2030 (Shi et al., 2018). As a typical example, China's rapid urban development resulted in massive energy consumption and CE that aggravated eco-environmental problems (Shi et al., 2019). Since China entered the period of rapid urbanization development, *urban sprawl* (US), in which the land urbanization rate grows faster than the population urbanization rate, has become a common problem among Chinese cities (Wu et al., 2021). For example, in 2012–2018, the growth rate of urban areas was 28.29%, but the urban population in China increased by 16.79%. US meant urban expansion outstripped the demand of the inhabitants, accompanied with the features of decentralization and low *population density* (PD) (Wang et al., 2020), which then affected energy consumption and CE (Chen et al., 2019).

Currently, since it cannot effectively quantify spatial US from a large-scale and long-time perspective, many studies tentatively explored *the*

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https://doi.org/10.1016/j.eiar.2021.106731
Received 8 September 2021; Received in revised form 18 December 2021; Accepted 21 December 2021
Available online 28 December 2021
0195-9255/

effect of US on CE (EUC) in a single city, stage, or region (Kakar and Prasad, 2020; Wang et al., 2019; Makido et al., 2012). Studies that simultaneously consider EUC within different city sizes, stages, and regions and its transmission factors remain scarce. Thus, our study aims to quantify and explore EUC from remotely sensed *nighttime light* (NTL) data by using 41 cities of Southwest China as experimental objects. The four specific research objectives are to: 1) reliably quantify US from the NTL data; 2) quantitatively evaluate how US can affect CE in 41 cities of Southwest China; 3) effectively explore whether EUC varies in cities with different city sizes, stages, and regions; 4) comprehensively investigate the transmission factors of EUC with various factors. The study will offer scientific references for a sustainable urban spatial structure and a low-carbon urban planning system in a country and provide a low-carbon sustainable development path for a global perspective of carbon neutral.

2. Literature review

2.1. Quantifying US

An accurate quantification of US is the premise for investigating EUC. Some studies have attempted to develop indexes such as average PD, single- and multi-dimension *US index* (USI) for measuring US (Yue et al., 2016; Gielen et al., 2018; Frenkel and Ashkenazi, 2008; Salvati and Carlucci, 2016; Cheng et al., 2020; Du et al., 2021). For example, Gielen et al. (Gielen et al., 2018) utilized Bayesian Factor Analysis to obtain a single USI, which allows to obtain the uncertainty of the inferred index, in contrast to traditional approaches. Frenkel et al. (Frenkel and Ashkenazi, 2008) developed a composite sprawl index that could assess urban sprawl dynamics in Israel. Salvati et al. (Salvati and Carlucci, 2016) experimented with 132 socioeconomic and environmental indicators to analyze the effect of different degrees of residential decentralization on cities. A few studies have also combined population data with built-up areas or average PD to construct a single index to reflect the extent of US (Cheng et al., 2020; Du et al., 2021). However, studies often constructed the US indexes on the basis of socioeconomic statistics (Guan et al., 2020). Lacking spatial information, the statistics cannot reflect the US changing spatial characteristics. Additionally, the statistics still have limitations, such as inconsistent scope, inconsistent caliber, restrictions by administrative units, and time lags. Therefore, emerging research methods should be utilized to effectively identify and quantify US.

Many studies have utilized optical remotely sensed images to assess US. For example, some different types of remotely sensed images, including the Landsat images, the IKONOS images, and the Sentinel-2 images, have been exploited in calculating the rates, extents, and patterns of US (Lu et al., 2019; Papadomanolaki et al., 2019). These approaches are cost-intensive and time-consuming, requiring many human, material, and financial resources to analyze US at large or multi-temporal scales. Considering that US not only reflects the change in urban areas but also is closely associated with socioeconomic development, capturing US by only using traditional optical remote sensing images or statistics is difficult.

Since nighttime lights are closely linked with human activities, NTL data that detect anthropogenic lights open a new sunroof on measuring the extent of US (Wu et al., 2020; Cheon and Kim, 2020). NTL data not only have the superiority of good continuity, accessibility, and independent objectives, but also avoid the one-sidedness, subjectivity, and poor replication among the different regions. Gao et al. (Gao et al., 2016) combined NTL data and statistics to monitor US effectively in China. However, studies have quantified US by only using the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) data updated from 1992 to 2013 (Bergantino et al., 2020; Sutton, 2003). The Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) data that have been published since 2012 have been limited to quantify US with the deficiencies of background noises and outliers. Because of the incongruousness between the two datasets, few studies have quantified US with a long-term series NTL data.

2.2. Evaluating EUC

Despite recent studies have explored the effects of US (Ewing, 2008; Carruthers and Ulfarsson, 2003; Sarkodie et al., 2020; Gielen et al., 2021; Chen et al., 2021), to date, the viewpoints on EUC remain controversial, mainly including the following three categories: aggravated effect, reduced effect, and nonlinear effect. For the aggravated effect, US can induce the prosperity of *the construction industry* (CI), aggravating CE (Kakar and Prasad, 2020). In addition, US can occupy green areas, thereby weakening the self-regulation ability of the ecosystem and intensifying *the urban heat island effect* (UH) that increases cooling energy consumption (Ewing, 2008; Mohan et al., 2020). Bart et al. (Bart, 2010) explored the climate change—US links in the EU member states in 1990–2000, and proved that US aggravated transport-related CE. Glaeser et al. (Glaeser and Kahn, 2010) confirmed that household GHG production would be reduced if the urban population lived in densely populated areas near urban centers. For the reduced effect, researchers believed that US can reduce CE from the incomplete combustion of vehicle fuel by alleviating traffic congestion through the reduction of PD in urban centers (Borck and Schrauth, 2021). US can also facilitate the dispersion of CE concentrations within cities by reducing the density of urban buildings. Glaeser et al. (Glaeser and Kahn, 2004) pointed out that sprawling cities tendentiously improve energy efficiency. Borck et al. (Borck and Schrauth, 2021) predicted that air pollution would be mainly concentrated in denser cities. Moreover, they expected that due to the interaction of the aggravated and reduced effect effects, the relationship would present a nonlinear trend. Han et al. (Han, 2020) found that the EUC is depicted as an inverted "U" curve and a "N" curve in the developed and underdeveloped Chinese provinces, respectively.

In addition, US and CE present differentiated characteristics which can lead to diversified relationships because of the differences between socioeconomic and natural environment. For example, Zarco-Soto et al. (Zarco-Soto et al., 2021) found that cities with larger population sizes exhibit more energy consumption and CE than those with smaller ones. Thus, whether EUC in different city sizes, stages and regions show different characteristics needs to be further explored.

2.3. Analyzing transmission factors

Although several studies have attempted to explored EUC, most of them have overlooked the transmission factors. Only a few studies explored the factors that affect CE and then analyzed the path to reduce CE. For example, energy consumption, industrialization, and population can positively affect CE (Xiong et al., 2019; Fan et al., 2006). By contrast, the improvement of technology, implementation of CE reduction policy, and industrial restructuring are conducive to CE reductions (Zheng et al., 2020).

It is inferred that US may affect CE through *the urban transport* (UT). Theoretically, US can alleviate the overconcentration of population in urban centers to an extent and slow down the traffic congestion in urban centers. However, it also lengthens the commuting distance and increases the commuting time. When lag is observed in the development of urban amenities, residents may prefer to use private cars, thereby causing the CE growth of UT. In addition, US may increase the demand for buildings and public infrastructure, resulting in the vigorous development of CI (Gielen et al., 2021). This is because CI can affect CE through the energy consumption of on-site construction operations and processes required to produce goods and service during construction operations. Construction activity can also drive the development of heavy industries that consume fossil fuels to provide the products for building operations, thereby contributing to large CE. Moreover, US may

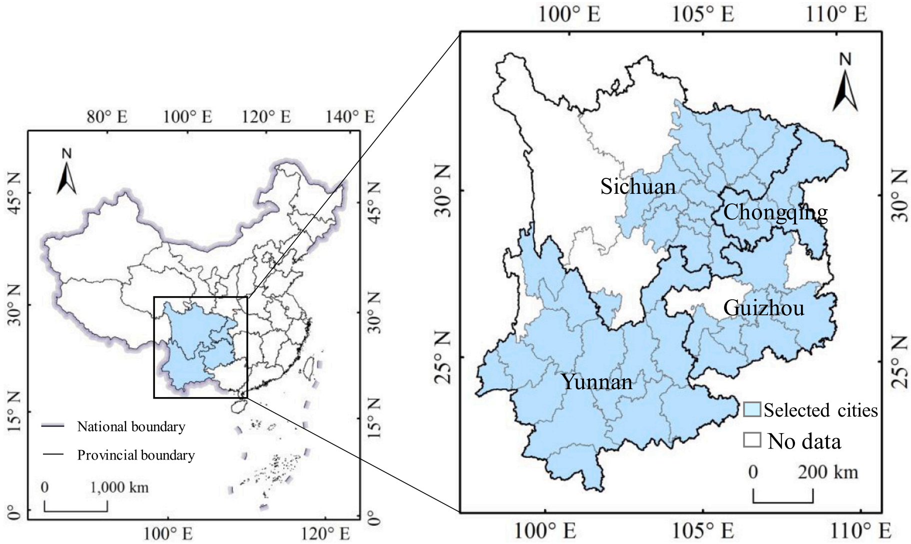

Fig. 1. Selected 41 cities in Southwest China. Note: Cities with abnormal or missing data were eliminated to ensure the continuity of data information. Chongqing was divided into four sub-units that were characterized by the population, economy, and natural environment.

intensify UH by occupying urban green areas. Urban green areas can reduce the greenhouse effect and improve air quality by absorbing carbon and other gases. When a city is sprawling, the effects of urban green space on pollution regulation and purification are continuously weakened, aggravating UH (Song et al., 2020). For cities situated in warm climates, UH greatly promotes energy demand and consumption increase to generate electricity for air conditioning refrigeration heating, increasing CE (Roxon et al., 2020). Overall, the final transmission effects of these factors depend upon the trade-off between their positive and negative effects. Whether US can affect CE through UT, CI, and UH needs further empirical research.

3. Data sources and methods

3.1. Study areas

41 cities of Southwest China were regarded as experimental objects in this study (Fig. 1). In 2019, the population of Southwest China was approximately 202.5 million, which accounted for 14.08% of China's total population. However, socioeconomic development presented an obvious spatial imbalance, causing an apparent socioeconomic inequality in cities of Southwest China. With economic growth and the deepening of targeted poverty alleviation policies, the rapid advancement of urbanization attracted many people who flooded into the urban areas. However, the urban built-up area's growth rate still exceeded that of the population, causing US (Wu et al., 2021). The rapid development of heavy industry in cities of Southwest China also led to the rapid growth of industrial CE. With significant quality-of-life changes, CE brought by motor vehicles and household consumption seriously increased.

Southwest China is a microcosm of the whole of China. It includes not only plain cities, mountainous cities, resource-based cities, and tourism service cities but also cities of different sizes, economic scales, and growth rates. Therefore, US in cities of Southwest China covers various sizes and regions within different natural and socioeconomic characteristics (Shi et al., 2020).

3.2. Data sources and data preprocessing

NTL data collected by DMSP-OLS from 2000 to 2013 and NPP-VIIRS from 2013 to 2018 were obtained from the NOAA/NGDC. DMSP-OLS data were acquired by six satellites that covered different stages and recorded surficial light radiance as 6-bit digital number (DN) values (0–63), with an approximate spatial resolution of 1 km. Two sets of DMSP-OLS data were available for the same year. The aging and switching of the observation satellites might have also reduced the comparability and continuity of data from different years. NPP-VIIRS monthly data recording the radiance of the earth's surface lights were limited by observation conditions, such as cloud cover and solar radiation at high latitudes in the summer. Obtaining valid radiance values everywhere is thus impossible. The lights produced by auroras, snow reflection, fires, and other transient sources might have disturbed the distribution of urban lights. Moreover, the spatial, radiometric, and spectrum resolutions of the NPP-VIIRS data are significantly improved compared with those of DMSP-OLS data (Li et al., 2020). Therefore, the two different series of NTL data must be corrected before constructing an integrated harmonized NTL dataset from 2000 to 2018. To build a consistent NTL dataset, taking the DMSP-OLS data from F16 in 2006 as the reference dataset, a quadratic model was employed to reduce the discrepancies in DMSP-OLS data (Liu et al., 2012). Then, noises and outliers in data were removed after averaging the NPP-VIIRS annual data (Wu et al., 2020; Zhao et al., 2017). Finally, a logarithmic model was constructed to develop the DMSP-OLS-like dataset (2000–2018) according to the two different series relationships. The accuracy verification results indicated that the average R^2 values of the regression between the gross domestic product (GDP) and the DMSP-OLS-like data were 0.88 and 0.81 at the city and county levels, respectively (Liang et al., 2020).

The CE data were acquired from the ODIAC fossil fuel emission dataset, which provided a high-spatial-resolution gridded product of 1 km. CE from fossil fuel combustion were estimated using NTL data and point or nonpoint data sources, which were highly accurate (Dobson et al., 2000).

The PD data were obtained from the LandScan dataset that estimated global population distributions and density at an approximately 1-km spatial resolution. The *impervious surface area* (ISA) data at a 30 m resolution were acquired from the database of Tsinghua University in China. The normalized difference vegetation index (NDVI) data were downloaded from *Google Earth Engine* (GEE). The annual NDVI data were obtained by the maximum synthesis method with a spatial resolution of 1 km. The *land surface temperature* (LST) data were also collected from GEE, and the averaged synthesis method was utilized to obtain the annual LST data with a 0.1° (approximately 11 km) spatial resolution.

The socioeconomic statistics include the following six indexes: GDP,

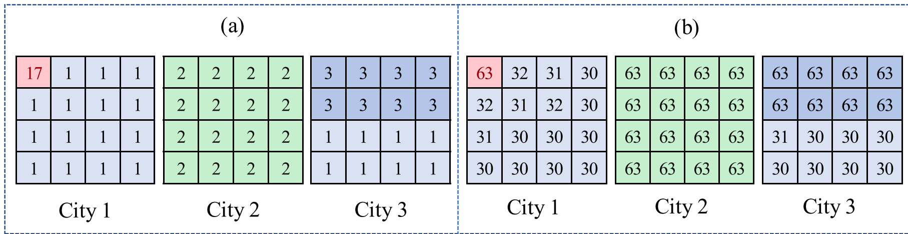

Fig. 2. (a) Urban population distribution; (b) urban DN value distribution.

the proportion of secondary industry GDP (GDP2), *the proportion of tertiary industry GDP* (GDP3), *the* per capita *GDP* (PGDP), *the proportion of total investment in fixed assets to GDP* (INV), *the gross construction output value* (GCOV), and *vehicle possession* (PV). They were collected from the Statistical Yearbook of Yunnan, Sichuan, Chongqing, and Guizhou (2001–2019) and the Statistical Yearbook of Chinese Cities (2001–2019).

3.3. Quantifying US from the NTL data

The premise and assumption of quantifying US from the NTL data were proposed as the following aspects.

- Usually, the average PD of statistics roughly measures the degree of US. However, distinguishing whether the distribution of the population was average or concentrated within an urban region is difficult. As shown in Fig. 2(a), the average PD of three cities is almost identical, but the urban spatial structure of City 1 appears sprawling, whereas that of City 3 is more compact. Thus, the density difference of the subdivided units within a city must be identified before quantifying US.
- The DN values of the NTL data can indicate socioeconomic activity intensities, and the luminous areas can reflect the space of urban areas and distribution of socioeconomic activities effectively (Wu et al., 2020). Moreover, the NTL data were continuously updated, enabling the long-term monitoring of urban spatial extension (Shi et al., 2014). The *average value of the DN values* (ADV) was employed to effectively identify the average intensity of socioeconomic activities. As shown in Fig. 2(b), if a pixel DN value is less than ADV, then it belongs to low-density urban areas; otherwise, it is a part of the high-density urban areas (Qin et al., 2016). The DN values of high- and low-density regions were extracted to evaluate the spatial dispersion of socioeconomic activities (e.g., US). Thus, both the intensity and area of urban sprawl can be considered and identified by the NTL data.

Based on the above theoretical analysis, an USI was developed for quantifying US according to the following steps. First, the luminous areas with the DN values ≥30 were extracted from DMSP-OLS data to represent urban areas (Li et al., 2020). The vertical USI was calculated according to the following formula (Qin et al., 2016):

$$\mathrm{SP_i} = 0.5 \times (\mathrm{L_i} - \mathrm{H_i}) + 0.5 \tag{1}$$

where SP_i is the vertical USI. L_i is the total NTL values of urban areas within a city where the DN values are lower than the ADV of the province, which accounts for the total NTL values of a city *i*. H_i is the proportion of urban areas where the DN value is greater than the provincial ADV. The numeric value, 0.5, obtained by multiple tests from the comparative analysis according to the study of Fallah et al. (Fallah et al., 2011).

Then, as shown in Fig. 2(a), the high- and low-density regions have the same population proportion, but the spatial structure of City 1 tends to be decentralized and exhibits low density. Thus, the horizontal USI can depict a spatial difference between the area's proportion of high- and low-density regions.

$$\mathrm{SA_i} = 0.5 \times (\mathrm{LA_i} - \mathrm{HA_i}) + 0.5 \tag{2}$$

where SA_i is the horizontal USI, LA_i is the proportion of area where the DN value in urban areas within a city is lower than the ADV of the province, and HA_i is the proportion of the area in which the DN value is higher than the provincial ADV.

Finally, by combining the decreasing intensity of socioeconomic activities and the dispersion of the scope of socioeconomic activities, the USI was calculated as follows:

$$USI_i = \sqrt{SA_i \times SP_i}, \tag{3}$$

where *USI* ranges from 0 to 1, and a larger value indicates that the city expanded in a more sprawling form.

3.4. Developing benchmark regression model

A benchmark regression model was developed to identify EUC. All variables were applied in the logarithmic transformation to avoid adverse effects caused by non-stationarity and heteroscedasticity. To avert a false regression, the unit root test and multiple collinearity test were used to examine the stationarity and collinearity, respectively. Thus, the following formula was developed:

$$CE_{it} = \beta_0 + \beta_1 USI_{it} + \beta_2 X_{it} + \zeta_{it} + \varepsilon_{it}, \tag{5}$$

where in year *t*, CE_{it} represents the average CE of city *i*, and β_0 is the intercept. The core explanatory variable USI_{it} represents the USI calculated by the NTL data, and its coefficient β_1 measures the elastic relationship between US and CE. If $\beta_1 >$ (or $<$) 0, then US will aggravate (or reduce) urban CE. *X* is a set of *control variable* (CV) vectors (i.e., PGDP, GDP2, GDP3, INV, NDVI, and PD). PD denotes the agglomeration of the population. INV represents the degree of urban infrastructure construction. NDVI defines the urban greening degree. PGDP, GDP2, GDP3 are used to measure the economy, industrialization, and upgrading of an industrial structure, respectively. ζ_{it} includes the city and year fixed-effects and is used to mitigate the error of missing variables and eliminate some endogeneity problems. ε_{it} is the random disturbance term.

3.5. Evaluating transmission mechanism

To test whether US can affect CE by influencing UT, CI, and UH. The models were developed as follows.

$$M_{it} = \alpha_0 + \alpha_1 USI_{it} + \alpha_2 X_{it} + \zeta_{1it} + \varepsilon_{1it}, \tag{6}$$

$$CE_{it} = \theta_0 + \theta_1 M_{it} + \theta_2 X_{it} + \zeta_{2it} + \varepsilon_{2it}, \tag{7}$$

where *M* denotes a transmission variable that represents three variables. In this model, three transmission factors (e.g., UT, CI, and UH) were represented by PV, GCOV, and LST, respectively (Salvati and Carlucci, 2016). α_1 represents the effect degree of US on transmission variable *M*, and θ_1 represents the effect degree of transmission variable *M* on CE. If $\alpha_1 <$ (or $>$) 0, then US has a negative (or positive) effect on transmission variable *M*. If $\theta_1 <$ (or $>$) 0, then transmission variable *M* has a negative (or positive) effect on CE.

Table 1
Results of the unit root test and multiple collinearity test.

Variable	LLC test		Fisher-ADF test		VIF	Tolerance
	Level	First difference	Level	First difference		
CE	−23.758***	−9.707***	381.849***	187.903***	–	–
GDP2	−4.678***	−17.416***	101.381*	391.063***	3.537	0.283
GDP3	−15.607***	−28.008***	141.308***	324.556***	2.948	0.339
INV	−3.654***	−22.607***	113.551***	394.233***	2.531	0.395
NDVI	−6.907***	−25.629***	194.060***	492.019***	1.625	0.616
PD	−5.323***	−20.982***	98.737	326.813***	1.606	0.622
PGDP	−2.548***	−22.512***	140.457***	414.657***	1.195	0.837
USI	−17.152***	−28.473***	286.371***	514.520***	1.039	0.963
Mean VIF	–	–	–	–	2.069	0.283

Note: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2
EUC of all sample cities in Southwest China.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	POLSM	POLSM	FEM	FEM	POLSM	FEM
USI	2.211 (1.115)	3.140** (2.050)	0.225 (0.723)	0.727** (2.274)		
l.USI					2.503* (1.721)	0.161 (0.531)
d.PD		−0.794 (−0.955)		−0.127 (−0.913)	−0.780 (−0.936)	−0.149 (−1.063)
PGDP		0.763*** (12.807)		0.152*** (3.842)	0.765*** (12.816)	0.148*** (3.721)
GDP2		1.338*** (6.299)		0.150*** (3.252)	1.350*** (6.356)	0.141*** (3.040)
GDP3		0.292 (1.373)		0.084 (1.586)	0.300 (1.411)	0.086 (1.615)
INV		−0.249*** (−4.323)		0.030** (2.254)	−0.247*** (−4.273)	0.029** (2.211)
NDVI		−4.108*** (−6.467)		−0.354 (−1.440)	−3.970*** (−6.363)	−0.353 (−1.427)
Constant	2.703*** (4.294)	−2.780*** (−4.171)	1.725*** (17.352)	0.895*** (3.865)	−3.008*** (−4.713)	0.741*** (3.253)
City	N	N	Y	Y	N	Y
Year	N	N	Y	Y	N	Y
Obs	779	738	779	738	738	738
R^2	0.002	0.527	0.920	0.917	0.526	0.916
F	1.244	116.3	435.8	307.8	115.9	305.4
Prob (F-statistic)	0.265	0	0	0	0	0

Note: Y represents yes; N represents no. Prob represents the probability. t-statistics in parentheses. *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. The same below.

4. Results

4.1. Benchmark regression model analysis

To avoid a pseudo regression, the Fisher–ADF and LLC tests were conducted to test the panel data stationarity (Table 1) (Levin et al., 2002; Maddala and Wu, 1999). In general, the rejection of the null hypothesis by the Fisher–ADF and LLC tests indicated the stability of the panel data sequence. According to the results, PD was insignificant in the Fisher–ADF test, and PD accepted the nonstationary null hypothesis at the level but rejected it at the first difference. The remaining variables were stationary at the level, and the nonstationary null hypothesis was rejected at the least 10% significance level. In addition, the multicollinearity examination showed that the average value of *the variance inflation factor* (VIF) was 2.069, and VIF for each variable was eligible (<10), among which the maximum VIF value of GDP2 was 3.537, which was far less than 10. Generally, no multicollinearity was observed among all variables.

To evaluate EUC more accurately, *the pooled ordinary least squares model* (POLSM) and *the fixed effect model* (FEM) were simultaneously established in the empirical benchmark analysis. Table 2 lists the regression results of EUC in all sample cities of Southwest China. In column (1), the USI coefficient was insignificant, but the sign was positive. Considering other factors, the estimation results still showed that the sign of USI coefficient was significantly positive and passed the 95% confidence test in column (2). Column (3) showed that the USI coefficient was positive but lacked significance. However, column (4) indicated that the USI coefficient was positive (0.727) and significant (5% level), implying that US had a positive effect on CE. Moreover, the lagged variable was introduced to alleviate the reverse causal and estimation biases in the panel regression. According to columns (5)–(6), the positive EUC still held after USI was lagged for one year. Although not all the USI coefficients shown in POLSM and FEM at the significance level of 10%, the coefficients of USI in all models were positive, indicating that US might promote the increase in CE. Specifically, US had a positive correlation with CE in columns (2), (3), and (4) with estimated coefficients of 3.140, 0.225, and 0.727, respectively. Theoretically, US would aggravate CE, that is, a 1% increment in the USI led to an increase in CE by 0.225%–3.140%. Based on the above results, it is indicated that US can aggravate CE in cities of Southwest China.

4.2. Robustness analysis

To enhance the robustness of the benchmark results, USI was replaced by an authoritatively *single-indicator US index* (SPR) which was calculated on the basis of statistical data (Cheng et al., 2020). Table 3

Table 3
Replacement of core explanatory variable for the robustness test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	POLSM	POLSM	FEM	FEM	POLSM	FEM
SPR	0.500***	0.192**	0.255***	0.008		
	(4.759)	(2.567)	(5.224)	(0.546)		
l.SPR					0.198***	0.004
					(2.681)	(0.272)
d.PD		−0.792		−0.155	−0.777	−0.155
		(−0.955)		(−1.114)	(−0.936)	(−1.107)
PGDP		0.747***		0.148***	0.747***	0.148***
		(12.495)		(3.711)	(12.493)	(3.704)
GDP2		1.356***		0.138***	1.367***	0.138***
		(6.401)		(3.006)	(6.453)	(3.004)
GDP3		0.336		0.086	0.341	0.086
		(1.579)		(1.617)	(1.604)	(1.612)
INV		−0.245***		0.029**	−0.241***	0.029**
		(−4.269)		(2.171)	(−4.195)	(2.199)
NDVI		−3.719***		−0.346	−3.695***	−0.350
		(−6.156)		(−1.400)	(−6.118)	(−1.414)
Constant	2.048***	−3.754***	2.025***	0.700***	−3.781***	0.697***
	(99.834)	(−8.269)	(251.424)	(3.230)	(−8.334)	(3.200)
City	N	N	Y	Y	N	Y
Year	N	N	Y	Y	N	Y
Obs	779	738	779	738	738	738
R^2	0.028	0.529	0.036	0.916	0.529	0.916
F	22.65	117.0	27.29	305.4	117.2	305.3
Prob (F-statistic)	2.32e-06	0	2.28e-07	0	0	0

Table 4
Robustness test of removing core city samples.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	POLSM	POLSM	FEM	FEM	POLSM	FEM
USI	8.190***	6.013***	0.189	0.657*		
	(4.217)	(3.843)	(0.558)	(1.904)		
l.USI					5.237***	0.027
					(3.539)	(0.083)
d.PD		−1.630*		−0.125	−1.546*	−0.156
		(−1.944)		(−0.740)	(−1.838)	(−0.925)
PGDP		0.555***		0.182***	0.555***	0.179***
		(8.685)		(4.249)	(8.662)	(4.179)
GDP2		1.156***		0.209***	1.189***	0.204***
		(5.460)		(4.091)	(5.622)	(3.971)
GDP3		−0.840***		0.100*	−0.816***	0.103*
		(−3.746)		(1.810)	(−3.642)	(1.861)
INV		−0.275***		0.037***	−0.269***	0.037**
		(−4.856)		(2.597)	(−4.761)	(2.576)
NDVI		−0.547		−0.025	−0.343	−0.016
		(−0.795)		(−0.089)	(−0.503)	(−0.058)
Constant	4.513***	1.421*	1.633***	0.621**	1.104	0.434*
	(7.332)	(1.891)	(15.124)	(2.475)	(1.530)	(1.769)
City	N	N	Y	Y	N	Y
Year	N	N	Y	Y	N	Y
Obs	703	666	703	666	666	666
R^2	0.025	0.479	0.914	0.912	0.477	0.911
F	17.78	86.29	361.7	260.5	85.69	258.8
Prob (F-statistic)	2.80e-05	0	0	0	0	0

lists the regression results. After replacing the core independent variable, the regression results were still similar to the original benchmark regression results. The SPR coefficients at the significance level of 1% proved that US aggravated CE in columns (1)–(2). In columns (3)–(4), although one of the SPR coefficients failed to pass the significance test, both were positive, implying that the intensification of US can still increase CE. Moreover, when SPR was lagged for one year, the positive EUC still held in columns (5)–(6).

Moreover, some special cities, such as core cities and municipalities, were removed from the estimation in a robustness test (Du et al., 2021). Compared with general cities, core cities in Southwest China, such as Kunming, Guiyang, Chengdu, and Chongqing metropolitan areas, had obvious preferences in economic dynamism, policy priority, political status, and financial capacity. These core cities, which were considered to represent the "image spokesperson" of the provinces, had green coverage and landscape LED lighting that tended to interfere with the lighting intensity within the central city, thereby affecting the accuracy of the distribution of urban socioeconomic activities reflected by the NTL data. Thus, the above-mentioned core city samples were removed in the model to avoid abnormal value interference. As listed in columns (1)–(2) from Table 4, the significance level of USI (8.190 and 6.013) at 1% proved that US continuously increased CE. Although USI coefficients were insignificant in columns (3)–(4), both were positive, suggesting that the deterioration of US increased CE. In addition, the positive EUC still held after USI was lagged by one year. Therefore, the above analyses supported the robustness of results.

Table 5
Correlations between USI and SPR.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: SPR					
	POLSM	POLSM	FEM	FEM	FEM	FEM
USI	6.129***	6.222***	4.931***	3.387***	1.329	2.108*
	(5.485)	(5.169)	(5.882)	(3.698)	(1.267)	(1.855)
Constant	−2.137***	−2.331***	−1.560***	−0.929**	0.245	−0.224
	(−3.970)	(−4.051)	(−3.863)	(−2.088)	(0.485)	(−0.406)
Controls	N	Y	N	Y	N	Y
City	N	N	Y	Y	Y	Y
Year	N	N	N	N	Y	Y
R^2	0.037	0.077	0.045	0.132	0.188	0.203
F-statistic	30.08	10.09	34.60	17.51	8.748	7.468
Prob (F-statistic)	5.60e-08	9.76e-11	6.15e-09	0	0	0

Table 6
EUC in cities within different city sizes.

Variables	Small city		Medium city		Large city	
	POLSM	FEM	POLSM	FEM	POLSM	FEM
	(1)	(2)	(3)	(4)	(5)	(6)
USI	4.584**	1.231**	2.427	0.369	2.264	0.442
	(1.978)	(2.051)	(1.174)	(0.638)	(1.205)	(1.384)
d.PD	−3.147*	0.044	−1.274	−0.357	0.484	−0.100
	(−1.754)	(0.130)	(−1.271)	(−1.211)	(0.597)	(−0.961)
PGDP	0.493***	0.319***	0.804***	0.178**	0.840***	−0.133***
	(4.884)	(5.264)	(9.560)	(2.175)	(11.845)	(−3.031)
GDP2	1.706***	0.347***	0.755***	0.258***	0.235	−0.113**
	(4.425)	(3.563)	(2.832)	(3.086)	(0.812)	(−2.545)
GDP3	−0.852**	0.023	0.647**	0.118	−0.239	−0.051
	(−2.303)	(0.243)	(2.091)	(1.186)	(−0.949)	(−0.980)
INV	−0.405***	0.043	−0.000	0.018	0.006	−0.011
	(−4.870)	(1.617)	(−0.001)	(0.723)	(0.070)	(−0.827)
NDVI	5.308***	−1.037**	−10.385***	0.438	−7.909***	−1.174***
	(5.707)	(−2.291)	(−9.279)	(0.909)	(−9.752)	(−5.026)
Constant	1.147	−0.152	−3.928***	0.584	−1.402*	2.798***
	(0.989)	(−0.420)	(−3.827)	(1.199)	(−1.873)	(11.599)
City	N	Y	N	Y	N	Y
Year	N	Y	N	Y	N	Y
Obs	234	234	288	288	216	216
R^2	0.648	0.943	0.544	0.882	0.751	0.979
F-statistic	59.55	135.6	47.78	77.05	89.53	348.6
Prob (F-statistic)	0	0	0	0	0	0

5. Discussion

5.1. USI provides an effective evaluation of US

The advantage of the NTL data makes it possible for quantifying US to enrich our understanding of the US environmental impact. The index can measure US in a low-cost and fast way from a lone-time and large-scale perspective when compared with the statistics and traditionally optical remotely sensed images. Given the US complexity, the USI can consider vertical and horizontal dimensions simultaneously.

To further verify the rationality of USI, a correlation analysis was developed between USI and SPR. If the regression results indicated a positive correlation between USI and SPR, then USI could replace SPR for subsequent empirical tests. Table 5 lists the quantitative test results of the relationships between USI and SPR. All results passed the significance test of F-statistic (>99% confidence). In columns (1)–(2), POLSM was used to assess the link between USI and SPR. The results showed that USI and SPR had a highly positive correlation, and the significance of *p*-value passed at a 1% level. In columns (3)–(4), FEM results without year-fixed-effects represented that USI had a positive correlation with SPR, and *p*-value passed the significance level of 1%. The bidirectional FEM regression results are shown in columns (5)–(6). The USI coefficient failed to pass the significance test (*p*-value >0.1), whereas USI was positively correlated with SPR in column (5). In column (6), USI and SPR had a highly positive correlation, and *p*-value passed the 10% significance test. Note that although various models had different regression results, USI always positively corresponded with SPR. Not all models were significant, but the *p*-value of USI in columns (1)–(4) and (6) was significant at the least 10% level, thus showing the rationality of the regression results. This proved the stable and positive correlations between USI and SPR. In general, USI is an important index for the application of nighttime light remotely sensed, and has the potential to be employed to quickly and reliably evaluate US and its environment impact.

5.2. EUC varies in cities of different city sizes, stages, and regions

To verify whether EUC varies in cities of different city sizes, stages, and regions, the city samples were firstly divided into three groups, namely, small cities (<0.7 million), medium cities (1.5 million), and large cities (>1.5 million), to analyze size heterogeneity. As the regression results indicated in Table 6, EUC varied among different sizes. For small cities, US had a significant effect on CE as the coefficients of USI passed significance at the 5% level. For medium cities, although the USI coefficients failed to pass the significance test, implying that US still had a positive effect on CE (Dong et al., 2020; Feng and Wang, 2020; Liu

Table 7
EUC in cities within different policy implementation stages.

Variables	2000–2009		2010–2018	
	POLSM	FEM	POLSM	FEM
	(1)	(2)	(3)	(4)
USI	7.164***	0.150	1.114	0.071***
	(3.060)	(0.370)	(0.492)	(4.398)
d.PD	−2.211	−0.916***	−0.741	−0.004
	(−1.237)	(−3.526)	(−0.821)	(−0.744)
PGDP	0.648***	0.128**	1.120***	−0.003
	(6.389)	(2.259)	(12.077)	(−1.300)
GDP2	2.037***	0.024	−0.181	0.009**
	(7.365)	(0.365)	(−0.495)	(2.103)
GDP3	0.732**	−0.125	−0.759**	0.001
	(2.356)	(−1.400)	(−2.429)	(0.150)
INV	−0.105	0.014	−0.330***	0.000
	(−1.195)	(0.585)	(−3.713)	(0.765)
NDVI	−1.223	0.176	−5.856***	0.020*
	(−1.303)	(0.486)	(−6.213)	(1.669)
Constant	−2.671***	1.413***	−0.862	2.122***
	(−3.085)	(4.401)	(−0.690)	(105.163)
City	N	Y	N	Y
Year	N	Y	N	Y
Obs	369	369	369	369
R^2	0.526	0.889	0.526	0.996
F-statistic	57.28	166.9	57.26	4793
Prob (F-statistic)	0	0	0	0

and Ai, 2016; Gelman and Stern, 2006). Although the signs were positive in large cities, USI coefficients lacked significance. The coefficients of US implied US was positively correlated with CE, thus, US might aggravate CE and the impact of US on CE varies with city sizes.

We found US in small cities had the strongest positive effect on CE, followed that in by large cities. The US in medium cities had the weakest positive effect on CE. Since the population expansion increased the energy consumption and CE in urban growth, the population size and PD of small cities failed to reach the level required by the agglomeration effect to generate positive externality benefits. Instead, they reduced the efficiency of energy use and increased CE caused by US. With the increase in city size, the concentration of socioeconomic activities can cause the agglomeration economic effect, improve energy use efficiency, and reduce environmental pressure (Gan et al., 2021), thereby generating positive externalities to reduce CE while offsetting part of the negative EUC and reducing CE. When the city size is too large, the mismatch between the urban environmental carrying capacity and the population size leads to a congestion effect, resulting in more energy consumption and CE while intensifying the severity of positive EUC.

In addition, the different stages of carbon reduction policies affected energy consumption and CE in Southwest China and led to the EUC heterogeneity. Basing on the data in different carbon reduction policy implementation stages (2000–2009 and 2010–2018), the temporal EUC heterogeneities was then identified in the next steps.

In 2009, China pledged to the international community at the Copenhagen Climate Summit that by 2020, carbon emission intensity would be reduced by 40%–45% from 2005 levels (Zhang, 2011). The year of 2009 was taken as the segmentation point and the periods 2000–2009 and 2010–2018 as the pre- and post-stages of CE in Southwest China, respectively. Table 7 presents the results for POLSM and FEM, which agreed with those in Table 2. However, the coefficients of USI varied in different stages. All coefficients of USI were positively correlated with CE in POLSM and FEM. More, EUC was greater in the pre-stage than that of the post-stage.

In response to the reduction target, the local governments were poised to adjust their energy policies and plan their reduction contribution (Wang et al., 2011). For the following year, the Chinese government incorporated energy conservation and emission reduction plans into the national strategic plan, promulgated various laws and regulations to clearly indicate the responsibilities of officials, and set corresponding binding targets in the Five-Year-Plan (Yuan et al., 2012). The series of policy measures showed China's determination to develop green transformation in the future. Consequently, the growth rate of total CE in Southwest China has slowed down significantly since 2009 (Zheng et al., 2019). Although the extent of US intensified, the government took effective measures, such as strictly setting up conditions for new cities and new districts, to control US so as to prevent the disorderly sprawl of urban boundaries, strengthen the development of municipal public service facilities, and increase the supply of basic public services (Central Committee of the Communist Party of China and State Council, 2014). The emergence of differences in the pre- and post-stages can be attributed not only to the differences in the mode and

Table 8
EUC in cities within different regions.

Variables	Guizhou		Sichuan–Chongqing		Yunnan	
	POLSM	FEM	POLSM	FEM	POLSM	FEM
	(1)	(2)	(3)	(4)	(5)	(6)
USI	0.711	1.083***	−3.136	0.571	−2.345	0.629
	(0.350)	(2.671)	(−1.624)	(1.157)	(−0.945)	(1.094)
d.PD	−0.129	0.063	0.066	−0.219	1.811	0.180
	(−0.106)	(0.311)	(0.088)	(−1.045)	(0.788)	(0.438)
PGDP	0.552***	0.406***	0.922***	0.026	1.002***	0.354***
	(4.521)	(6.010)	(12.540)	(0.273)	(9.347)	(5.880)
GDP2	2.158***	0.159**	0.617**	0.119	0.439	0.063
	(6.568)	(2.165)	(2.143)	(1.504)	(1.239)	(0.863)
GDP3	2.454***	0.325***	−0.150	0.050	−0.675*	−0.017
	(5.495)	(3.753)	(−0.632)	(0.546)	(−1.715)	(−0.166)
INV	−0.400***	−0.043	−0.215***	0.018	−0.427***	0.030
	(−3.012)	(−1.395)	(−2.962)	(0.599)	(−5.194)	(1.018)
NDVI	−4.907***	0.130	−9.652***	−0.764**	1.239	−1.202**
	(−4.010)	(0.302)	(−12.829)	(−2.091)	(1.331)	(−2.410)
Constant	−7.089***	0.118	−4.196***	1.502***	−1.859*	0.025
	(−7.626)	(0.384)	(−5.355)	(3.090)	(−1.726)	(0.072)
City	N	Y	N	Y	N	Y
Year	N	Y	N	Y	N	Y
Obs	126	126	342	342	270	270
R^2	0.814	0.984	0.716	0.902	0.489	0.944
F-statistic	73.81	246.2	120.1	114.8	35.80	161.6
Prob (F-statistic)	0	0	0	0	0	0

Table 9
UT transmission analysis.

Variables	POLSM				FEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PV	CE	PV	CE	PV	CE	PV	CE
USI	−0.035 (−0.050)		0.143 (0.046)		−0.033 (−0.064)		3.025* (1.947)	
PV		−0.487 (−0.561)		−0.180 (−0.242)		0.005* (1.769)		0.015* (1.748)
Constant	1.241** (2.542)	5.261*** (4.781)	−0.638 (−0.288)	11.237** (2.311)	1.150*** (3.225)	4.657*** (1345.642)	0.162 (0.077)	4.625*** (44.648)
Controls	N	N	Y	Y	N	N	Y	Y
City	N	N	N	N	Y	Y	Y	Y
Year	N	N	N	N	Y	Y	Y	Y
Obs	94	94	68	68	94	94	68	68
R^2	0.000	0.003	0.173	0.701	0.658	0.991	0.928	0.988
F	0.00253	0.315	1.788	20.12	25.39	1500	49.13	300.2

development of the regional social economy and the industrial focus in different stages but also to the transformation of the national and regional development strategies.

The natural conditions, resource endowments, and cultural beliefs of different regions vary greatly, causing differences in the extent of US and socioeconomic development. To explore whether EUC varied in different regions, the regressions were analyzed by the sub-samples of three geographical regions (i.e., Guizhou, Sichuan–Chongqing, and Yunnan). As listed in Table 8, the estimation results of the sub-samples in Guizhou implied that US aggravated CE as the signs of the regression coefficients were both positive. In column (2), the USI coefficient was significance at the 1% level. In Sichuan–Chongqing and Yunnan, the FEM results were contrary to those of POLSM, leading to inconsistencies in the estimates. This is because POLSM ignored heterogeneity between individuals, which was a factor associated with the explanatory variables. According to the study of Fernandez et al. (Fernandez Kranz et al., 2015), FEM required weaker assumptions than POLSM to obtain a consistent estimator. If the consistent assumption of POLSM was satisfied, then the FEM estimate should also be a consistent estimate, and POLSM and FEM would be close. If FEM was significantly different from POLSM, then the fixed-effects must be controlled, and FEM should be used. Although not all the elastic USI coefficients were statistically significant, the signs were positive. Therefore, the FEM results were regarded as the basic results exploring EUC in Sichuan–Chongqing and Yunnan. The coefficients of USI in FEM suggested that US was detrimental for the reduction of CE in different regions. In Guizhou, the USI modulus, which indicated the extent of EUC, was the largest, followed by Yunnan. The US in Sichuan–Chongqing had the weakest positive effect on CE.

Since the urban functions of Sichuan–Chongqing were relatively perfect, the government had actively controlled sprawl throughout the cities, reasonably planning the cities' layout. As the urbanization development appeared more coordinated and actively implemented the national policy, the positive EUC was relatively weak in Sichuan–-Chongqing. The urbanization rate in Guizhou and Yunnan was relatively low, and the urban development potential in these regions was great. US stimulated the development of the secondary industry in Guizhou and Yunnan in their pursuit of economic growth, aggravating CE.

5.3. *US can aggravate CE through UT, CI, and UH*

The above analysis showed that US had a positive effect on increasing CE. What were the transmission factors by which US affected CE? First, US lengthened the commuting distance between homes and the workplace, and as public transport failed to meet the needs of commuters, more commuters turned to private cars to meet their daily commuting demands. Thus, US might increase CE from UT. The average energy consumption and CE of private cars were 10 times more than those of public buses and approximately 20 times those of rail transit. The findings meant that although private cars improved the convenience of the residents' travel, they also increased energy consumption and CE. Thus, the above mechanism was verified as follows. Table 9 reports the empirical results for the POLSM and FEM through UT in Southwest China. Considering that the influence of US on the use of private cars was actually affected by many external factors, we focused on the POLSM and FEM with CVs. Compared with POLSM, FEM can evaluate the relationship more accurately because the disturbance factors interfere with the estimation of the parameters. In columns (7)–(8), US had a significant promoting effect on PV, and PV had a positive effect on CE, indicating that US could improve UT and then increase urban CE, which

Table 10
CI transmission analysis.

Variables	POLSM				FEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GCOV	CE	GCOV	CE	GCOV	CE	GCOV	CE
USI	6.477*** (5.012)		3.845*** (3.899)		2.352*** (4.460)		1.448*** (3.015)	
GCOV		1.230*** (25.163)		0.911*** (14.685)		0.265*** (8.385)		0.210*** (5.591)
Constant	10.479*** (11.068)	−2.560*** (−9.064)	0.177 (0.176)	−0.224 (−0.216)	3.344*** (8.650)	2.333*** (14.438)	−4.121*** (−4.884)	0.651 (0.964)
Controls	N	N	Y	Y	N	N	Y	Y
City	N	N	N	N	Y	Y	Y	Y
Year	N	N	N	N	Y	Y	Y	Y
Obs	570	570	540	540	570	570	540	540
R^2	0.042	0.527	0.536	0.669	0.864	0.924	0.893	0.916
F	25.12	633.2	87.88	153.8	174.2	333.4	169.1	222.3

Table 11
UH transmission analysis.

Variables	POLSM				FEM			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LST	CE	LST	CE	LST	CE	LST	CE
USI	0.491*		0.093		0.013		0.000	
	(1.838)		(0.343)		(0.319)		(0.007)	
LST		1.584***		2.624***		0.267		0.438
		(6.098)		(14.166)		(0.969)		(1.634)
Constant	3.126***	0.225	4.615***	−20.989***	2.719***	3.078***	2.806***	0.391
	(16.005)	(0.312)	(16.944)	(−16.507)	(87.833)	(4.091)	(36.552)	(0.433)
Controls	N	N	Y	Y	N	N	Y	Y
City	N	N	N	N	Y	Y	Y	Y
Year	N	N	N	N	Y	Y	Y	Y
Obs	779	779	738	738	779	779	738	738
R^2	0.004	0.046	0.200	0.627	0.567	0.920	0.527	0.916
F	3.378	37.19	26.02	175.3	49.57	436.1	31.29	306.6

was not conducive to the implementation of emission reduction. The development of public transportation was an important way to reduce transport CE.

US decreased PD and expanded the sphere of economic activities, which increased residents' demands for buildings, thus promoting the development of CI, such as real estate development. Specifically, CI could affect CE through the energy consumption of on-site construction operations. CI could also drive the development of heavy industries, such as the cement and steel industries. These industries consumed large amounts of fossil fuels to produce the products, thus contributing to large CE. Based on a world environmental input–output table in 2009, Huang et al. (Huang et al., 2017) discovered the total CE caused by global construction activities and found that the total CE of global construction was 5.7 billion tons, which accounted for 23% of the total CE generated from global economic activity.

POLSM and FEM were then used to detect whether CI had an essential role in US aggravating CE. Table 10 shows the empirical results. In the following models, US positively affected GCOV and exceeded the 1% significance test (>99% confidence). In the corresponding empirical model, GCOV held a significant positive correlation with CE. The above analysis revealed a significant positive link between US and GCOV and between GCOV and CE. Therefore, the test further confirmed that US affected CE by the action path of CI.

Moreover, the development of urban green areas was the most natural and effective measure to relieve UH. However, US unduly destroyed the surrounding green belt and waters and transformed the natural land surface into artificial landscape architecture, changing the cities' underlying surface and weakening the regional ecological regulating function. UH with the development of US directly affected the thermal comfort of the human body as well. To maintain the comfort of the human body, people used air conditioning and consumed a large amount of energy, which substantially increased the cooling energy consumption and CE in summer and threatened the livability and sustainable development of the cities.

As listed in Table 11, some the estimated coefficients of USI failed to pass the 90% confidence level, but the coefficients were all positive, implying that US positively affected LST. Therefore, US promoted the increase in LST. Although the elastic coefficients of LST lacked significance, the positive coefficients still indicated that LST might promote the level of CE.

In general, the above analysis confirmed that US could aggravate CE through UT, CI, and UH.

6. Conclusions

The study assessed EUC through empirical evidence from 41 cities in Southwest China. The results indicated that US could be effectively quantified by the NTL data. US could aggravate CE, and the robust analyses further confirmed the positive effect of US on aggravating CE. Heterogeneity evaluations also showed that US in cities within different city sizes had different positive effects on CE. The positive EUC was greater in pre-stage than that in post-stage and varied in three geographic regions. Quantitative analyses revealed that US could aggravate through UT, CI, and UH.

The study extends the following suggestions according to the findings. China's urban over-expansion and chaotic sprawl phenomenon hindered the further urban development and the construction of an ecological civilization. Feasible controls should be carried out in urban boundary planning for avoiding the excessive expansion and disorderly sprawl to achieve the goals of sustainable urban development and ecological civilization construction. Strategies should be implemented to mitigate the extent of US, conserve energy, and reduce emission. Moreover, the degree of urban agglomeration should be reasonably given full play to the positive externalities of the urban agglomeration economy. On the one hand, urban agglomeration can shorten urban traffic flow and commuting traffic times, thereby improving the operational efficiency of public service facilities between office and residential areas. On the other hand, urban agglomeration makes the resource allocation of urban functional areas more sensible. This consequently reduces the overall cost of living and energy consumption per unit of output for residents, lessen CE and other pollution emissions, and improve the environmental quality of urban areas. As the severity of EUC varies for cities with different policy backgrounds and development levels, governments need to formulate reasonable urban agglomeration plans and implement emission reduction strategies according to local conditions.

Author contributions

Yizhen Wu collected and processed the data, and wrote the manuscript.

Chuanlong Li collected and processed the data, and wrote the manuscript.

Kaifang Shi conceived and designed the study, and wrote the manuscript.

Shirao Liu collected and processed the data.

Zhijian Chang collected and processed the data.

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.

Acknowledgements

This work was supported by the Chongqing Social Science Planning Project (2021NDQN39), and the National Natural Science Foundation of China (42101345). We would like to thank Prof. Qingyuan Yang from Southwest University, China for her helpful suggestions on the paper. We also want to express our respects to the anonymous reviewers and editors for their valuable comments on improving the quality of the paper.

Appendix A. Abbreviations

ADV	Average value of the DN values
CE	Carbon dioxide emissions
CI	The construction industry
CV	Control variable
DN	Digital number
DMSP-OLS	Defense Meteorological Satellite Program's Operational Linescan System
EUC	The effect of US on CE
FEM	The fixed effect model
GCOV	The gross construction output value
GDP	Gross domestic product
GDP2	The proportion of secondary industry GDP
GDP3	The proportion of tertiary industry GDP
GEE	Google earth engine
GHG	Greenhouse gas
INV	The proportion of total investment in fixed assets to GDP
ISA	Impervious surface area
LST	Land surface temperature
NPP-VIIRS	Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite
NDVI	Normalized difference vegetation index
NTL	Nighttime light
PD	Population density
PGDP	The per capita GDP
POLSM	The pooled ordinary least squares model
PV	Vehicle possession
SPR	Single-indicator US index
UH	The urban heat island effect
US	Urban sprawl
USI	US index
UT	The urban transport
VIF	Variance inflation factor

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