The need for urban form data in spatial modeling of urban carbon emissions in China: A critical review

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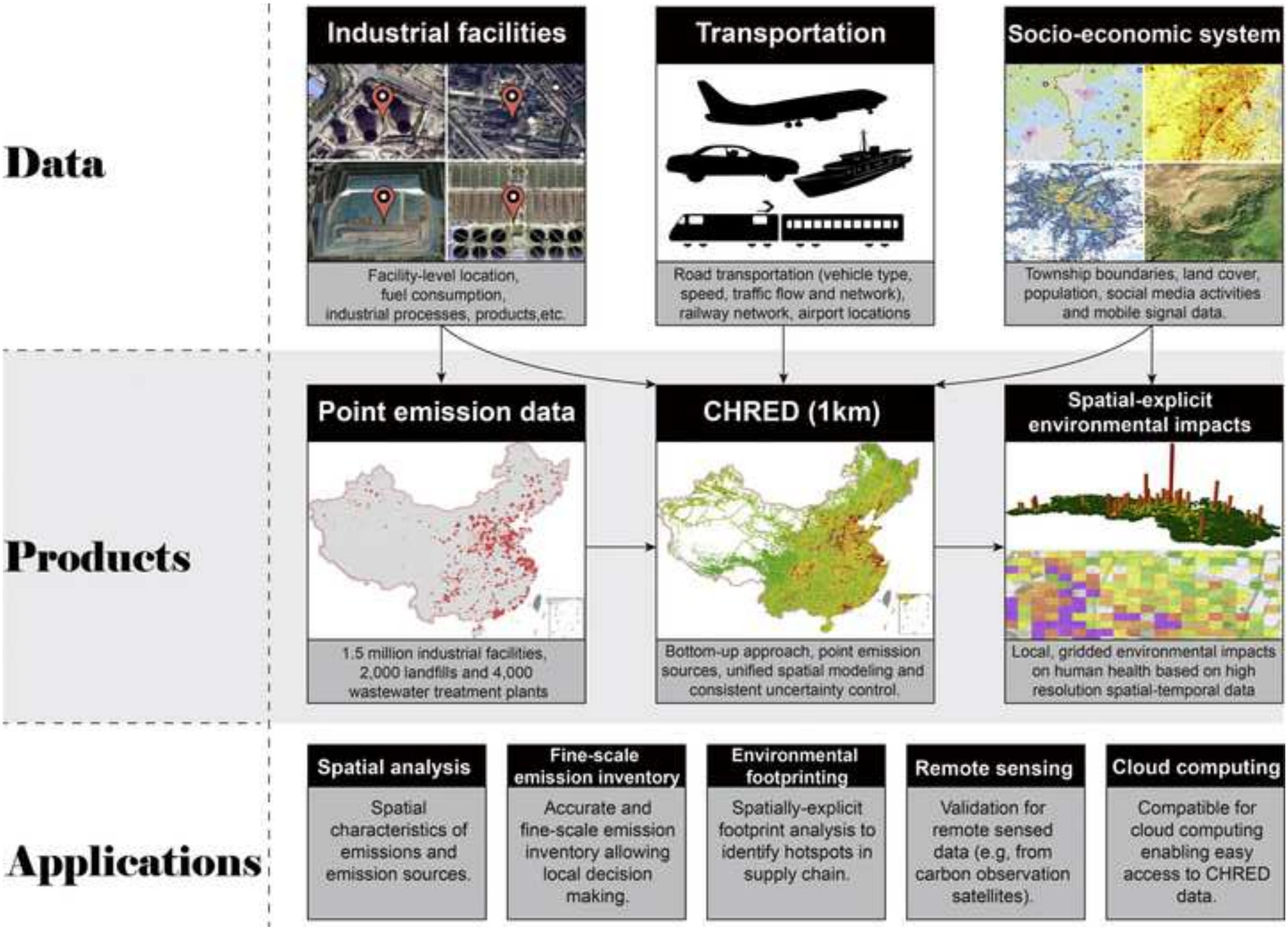
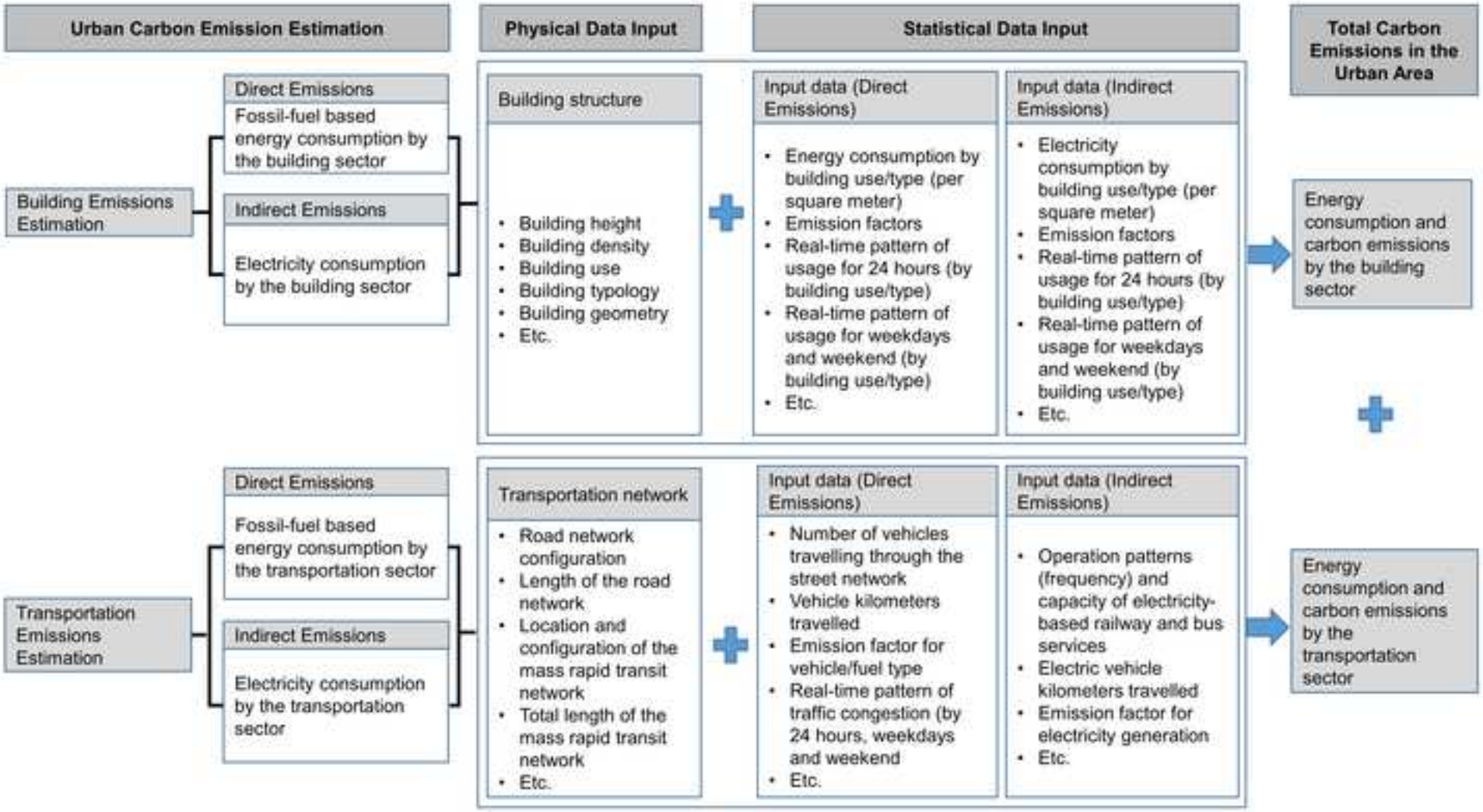

Data
Industrial facilities
Facility-level location, fuel consumption, industrial processes, products,etc.
Transportation
Road transportation (vehicle type, speed, traffic flow and network), railway network, airport locations
Socio-economic system
Township boundaries, land cover, population, social media activities and mobile signal data.
Products
Point emission data
1.5 million industrial facilities, 2,000 landfills and 4,000 wastewater treatment plants
CHRED (1km)
Bottom-up approach, point emission sources, unified spatial modeling and consistent uncertainty control.
Spatial-explicit environmental impacts
Local, gridded environmental impacts on human health based on high resolution spatial-temporal data
Applications
Spatial analysis
Spatial characteristics of emissions and emission sources.
Fine-scale emission inventory
Accurate and fine-scale emission inventory allowing local decision making.
Environmental footprinting
Spatially-explicit footprint analysis to identify hotspots in supply chain.
Remote sensing
Validation for remote sensed data (e.g, from carbon observation satellites).
Cloud computing
Compatible for cloud computing enabling easy access to CHRED data.


Urban Carbon Emission Estimation
Physical Data Input
Statistical Data Input
Total Carbon Emissions in the Urban Area
Building Emissions Estimation
Direct Emissions
Fossil-fuel based energy consumption by the building sector
Indirect Emissions
Electricity consumption by the building sector
Building structure
• Building height
• Building density
• Building use
• Building typology
• Building geometry
• Etc.
Input data (Direct Emissions)
• Energy consumption by building use/type (per square meter)
• Emission factors
• Real-time pattern of usage for 24 hours (by building use/type)
• Real-time pattern of usage for weekdays and weekend (by building use/type)
• Etc.
Input data (Indirect Emissions)
• Electricity consumption by building use/type (per square meter)
• Emission factors
• Real-time pattern of usage for 24 hours (by building use/type)
• Real-time pattern of usage for weekdays and weekend (by building use/type)
• Etc.
Energy consumption and carbon emissions by the building sector
Transportation Emissions Estimation
Direct Emissions
Fossil-fuel based energy consumption by the transportation sector
Indirect Emissions
Electricity consumption by the transportation sector
Transportation network
• Road network configuration
• Length of the road network
• Location and configuration of the mass rapid transit network
• Total length of the mass rapid transit network
• Etc.
Input data (Direct Emissions)
• Number of vehicles travelling through the street network
• Vehicle kilometers travelled
• Emission factor for vehicle/fuel type
• Real-time pattern of traffic congestion (by 24 hours, weekdays and weekend
• Etc.
Input data (Indirect Emissions)
• Operation patterns (frequency) and capacity of electricity-based railway and bus services
• Electric vehicle kilometers travelled
• Emission factor for electricity generation
• Etc.
Energy consumption and carbon emissions by the transportation sector

Highlights

- The spatial modeling studies of urban carbon emission in China are reviewed.
- The available data and methods are summarized.
- The strengths and weaknesses of the methods are compared.
- Urban forms can affect urban carbon emissions.
- Future developments will require a finer spatial resolution and urban form data.

The need for urban form data in spatial modeling of urban carbon emissions in China: A critical review

Word count: 11627

Abstract:
Cities produce over 70% of global carbon emissions and are thus crucial in driving climate change. Urban carbon emissions may continue to increase especially in those less-developed countries and regions which are still under rapid urban development. Policymakers need to find ways to effectively control and reduce carbon emissions. Thus, spatial modeling methods to map and predict urban carbon emissions have been developed to meet these needs. This paper examines the progress of the spatial modeling of carbon emissions and the relationship between urban form and carbon emissions in China by reviewing more than 100 peer-reviewed journal articles in the Scopus database. The latest prediction methods and techniques are described in the paper. Their advantages and limitations are then discussed.

Urban forms have a significant influence on carbon emissions and have been applied in spatial modeling studies in other countries. However, this review has identified the lack of urban form data and high-resolution inventories from existing studies in China. Future developments in the spatial modeling in China should therefore have a fine spatial resolution and incorporate open and high-quality urban form data, including urban morphology and land use/land cover.

Keywords: urban carbon emissions, spatial modeling, systematic review, urban form, China.

1. Introduction

Carbon dioxide (CO_2) is the principal anthropogenic greenhouse gas (GHG) and the major cause of climate change (IPCC, 2007). The global atmospheric CO_2 concentration has risen from about 280 ppm before industrialization to 409.8 ppm in 2019 (Lindsey, 2020). To achieve the goal of controlling temperatures for climate change mitigation, carbon emissions need to be significantly reduced (Pachauri et al., 2014). Cities contribute 71%-76% of global carbon emissions from energy activities, so they are the major focus for carbon emissions mitigation (Pachauri et al., 2014). The world population from 2012 to 2050 is anticipated to rise mainly in cities according to the United Nations population estimate (UN DESA, 2018). Global carbon emissions are foreseen to grow due to the projected urban development. Since urban carbon emission inventory is the foundation for attempts to mitigate carbon emissions, policymakers and the scientific community have made significant efforts to establish carbon emission inventories to deal with climate change. Most previous investigations

on emission modeling used production-based statistics at the administrative units level (e.g. provincial or city level) based on Intergovernmental Panel on Climate Change (IPCC) or provincial-level Guidelines (Clarke-Sather et al., 2011; Shan et al., 2017). Although the inventories are authoritative, the spatial variations and the energy consumption within the administrative unit cannot be revealed, which limits their further impact on the interdisciplinary actions to climate change mitigation (Cao et al., 2014).

The spatial modeling of urban carbon emissions can facilitate the development of spatially distributed emission inventories and reveal the spatial patterns within an administrative unit (Ou et al., 2015b). These inventories can provide a spatial visualization of the carbon emissions from both production and consumption, enabling the practical and realistic assessment of emission mitigation, such as identifying the carbon emission hotspots, energy activities responsible for high emissions, etc. (Kanemoto et al., 2016). They can also be integrated with other spatial data to facilitate interdisciplinary cooperation to reduce carbon emissions. Consequently, a variety of approaches have been developed and used to spatially model the carbon emissions in different cities (Cai et al., 2018b; Doll et al., 2000; Wang, J. et al., 2014).

China has been industrializing and urbanizing at an accelerating pace since the beginning of its reform and opening in 1978. The rapid development has unavoidably caused massive carbon emissions which impeded the sustainable development of China and impacted the global climate (Paltsev et al., 2012). China has become the country that emits the highest amount of carbon emissions in the world since 2006 (Netherlands Environmental Assessment Agency, 2007). Moreover, China's carbon emissions are predicted to keep increasing until 2025 as a consequence of the continuous industrial transformation and economic growth (Zhou et al., 2019). Consequently, the Chinese government has set ambitious GHG mitigation targets and pledged to be carbon neutral by 2060 (Wang, 2009; Xinhua, 2020).

The development of the spatial inventory of carbon emissions can therefore serve as a cutting-edge tool for governments at different levels to meet China's timely need for achieving carbon neutrality. Besides, urban development is a vital element for carbon emission and its reduction. City planning and space optimization policies, particularly those targeting urban form, are growingly significant in carbon emissions control and mitigation (Wang et al., 2015). In order to further develop our knowledge in controlling and reducing carbon emissions for China, it is necessary to review the past developments and studies on the spatial modeling of carbon emission to understand their capabilities, advantages, and limitations. A comprehensive understanding of the influence of urban forms on carbon emissions is also essential for the implementation of low carbon strategies in China.

Therefore, this study aims to perform a systematic review to synthesize the available literature on 1) the existing methodologies and data for the spatial modeling of urban carbon emissions in China, and 2) the relationship between the urban form and carbon emissions in China. This study is the first one to review the spatial inventories of urban carbon emissions in China. Previous reviews on CO_2 inventories generally focused on the statistical approach (Chen et al., 2017; Yang et al., 2016). Although they pointed out the shortcomings of the existing statistical approach in China, this manuscript will provide new insights and perspectives beyond existing reviews since it investigates the spatial inventories within a city boundary, which can support the control and mitigation of carbon emissions regarding urban planning and space optimization strategies. Moreover, this study will identify the limitations of the current studies to recommend future directions of the spatial inventories.

Therefore, the major objectives are determined:

- To select and document the relevant and the most up-to-date peer-reviewed journal articles in the Scopus database;
- To identify the key methodologies and developments in the spatial modeling of carbon emissions;
- To explore the relationship between the urban forms and the carbon emissions;
- To analyze the strengths and weaknesses of the reviewed spatial models;
- To review and discuss their current applications and limitations;
- To explore the future needs and trends in the spatial model development.

2. Methodology

Systematic reviews are considered to be the most impartial and efficient method for analyzing existing scientific research (Haddaway et al., 2015). Hence, we performed a systematic review of the research projects and studies on the spatial modeling of China's urban carbon emissions. We adopted the procedure of the PRISMA Statement form (Moher et al., 2009) which has been applied in many urban studies (Asadzadeh et al., 2017). There are four stages of the PRISMA Statement: Identification, Screening, Eligibility, and Analysis (Moher et al., 2009).

Under the Identification process, keywords were used to search the literature database and identify possibly related studies. Scopus was chosen as the search engine in this study because it focuses on peer-reviewed academic articles and covers a broad scope of multi-disciplinary fields. Only peer-reviewed articles were identified as relevant studies in this review.

The identification in this study mainly contains two categories, category 1 is the searching on spatial modeling of urban carbon emissions in China, category 2 is about the relationship between urban forms and carbon emissions (Table 1). Keywords A

contains the keywords that were used for both two categories. To incorporate all the available literature in the database, “carbon emissions” and all the synonyms of carbon emissions such as “CO_2 emission” OR “carbon dioxide emission” OR “greenhouse gas emission” were used in keywords A. Also, the study area “China” was used to limit the search results. Keywords B includes the keywords which are only used in one category. In category 1, the keywords “spatial modeling” OR “mapping” were incorporated into the search criteria to filter the papers relevant to the development of spatial inventories. “Urban” OR “city” was also included in the keywords to filter the research focusing on fossil fuel carbon emissions from transport, business, residential and industrial sectors. For the searching of literature in category 2, the keyword “urban form” was added to the searching engine. The identification process based on the selected keywords was performed for the article title, abstract, and keywords of the papers. Also, this study covered the most up-to-date literature as of May 2021.

During the process of screening, the acquired literature that is not relevant to this study was removed by manually checked the titles, abstracts, and keywords. All the obtained records were screened to exclude duplicate and unrelated documents. Thirdly, all the records after the previous two steps were examined completely to select the most relevant results, including the main text and the references. Finally, the necessary information on the related literature was extracted, processed, and synthesized in the analysis step.

Table 1. Summary of all the keywords used during the identification phase.

Categories	**Keywords A**	**Keywords B**
1. Urban carbon emissions mapping in China	“carbon emission” OR “CO2 emission” OR “carbon dioxide emission” OR “greenhouse gas emission” AND “China”	AND (“spatial modeling” OR “mapping”) AND (“urban” OR “city”)
2. The relationship between urban forms and carbon emissions		AND “urban form”

3. Results

3.1 Overall results

After the searching and analysis steps, there are 106 papers in total, where 82 papers are in category 1 and 24 papers are in category 2. For category 1, the results were mainly classified based on the methods. It can be found that there are four commonly used methods: 1) top-down analyses that assign the emissions from a coarse spatial unit to a

finer resolution; 2) bottom-up models that aggregate the fine emission data such as point source emissions to the desired spatial grid (Cai et al., 2018b; Wang, J. et al., 2014); 3) carbon satellite observations which convert the CO_2 concentration from carbon satellites; and 4) hybrid method involving both bottom-up and top-down approach. For category 2, the urban form can be described in terms of land use/cover and urban morphology (Ren et al., 2017). Therefore, the retrieved literature in category 2 was categorized into the impact of urban morphology and the impact of land use/land cover characters.

3.2 top-down method using nighttime lights

3.2.1 data and adjusted indexes

Top-down methods allocate the carbon emissions within a large spatial unit to a high spatial resolution by adopting some algorithms or proxy data such as land use (Chuai and Feng, 2019), road length (Song et al., 2020). With the development of remote sensing techniques, the nighttime light (NTL) data have been the most frequently used proxy to distribute the statistical carbon emissions at the jurisdiction level. The NTL is a kind of satellite observation and derivative product to detect man-made lights, hence offering a unified, spatially explicit, continuous, and prompt monitoring of the earth's surface during nighttime (Elvidge et al., 1997; Elvidge et al., 2013). Previous research has indicated that the NTL data can potentially reflect the socioeconomic conditions and human activities that are relevant to energy demand (Doll et al., 2000; Small et al., 2005; Sutton et al., 2001). Moreover, there is an assumption that the brightness value of the NTL is positively correlated to the carbon emissions produced by energy activities of the same pixel (Han et al., 2018). Hence, the NTL is capable of detecting urban carbon emission variations in both spatial and temporal dimensions when combined with statistical emission data.

The Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) launched in 1992, is the most widely used NTL data in the spatial modeling of carbon emissions due to its long time span (Lu et al., 2018; Meng et al., 2014; Shi et al., 2016; Wang and Li, 2016). Nevertheless, the DMSP data have a few notable disadvantages (Doll et al., 2000; Elvidge et al., 2010): low spatial resolution of 30 arc seconds, oversaturation problems on bright lights in urban areas, blooming effect with the lights scattered from built-up areas into areas without light, etc. These shortcomings may diminish the correlation between human activities and NTL products (Letu et al., 2010), leading to increased uncertainties in the modeling of carbon emission in certain regions, especially in large urban cores with strong artificial lighting (Letu et al., 2011; Raupach et al., 2010). The global radiance calibrated DMSP NTL data have been developed by the Earth Observation Group in National Oceanic and Atmospheric Administration's National Geophysical Data Center (NOAA/NGDC) to solve these

issues (Ziskin et al., 2010). However, there are only a few images that have been calibrated so far, limiting the application of time-series analyses of the product (Ma et al., 2014).

The satellite Visible Infrared Imaging Radiometer Suite onboard the Suomi National Polar-Orbiting Partnership (NPP-VIIRS) was developed as a brand-new source of NTL image by the NOAA/NGDC in 2011 (Elvidge et al., 2013). The new NTL data have several advancements compared to the previous DMSP-OLS product (Elvidge et al., 2013) (Table 2). The spatial grid of the NPP-VIIRS data is finer (15 arc-second). Also, the NPP-VIIRS product has already been calibrated on the satellite (Elvidge et al., 2013). Moreover, the oversaturation issue does not exist in the NPP-VIIRS due to its more sensitive day/night spectral band, which can greatly enhance the capability of identifying artificial lighting (Liao et al., 2013).

Table 2. Characteristics of DMSP-OLS and NPP-VIIRS

Satellite	**Spatial resolution**	**Bands**	**Period**	**Onboard calibration**	**Saturation**
DMSP-OLS	30 arc seconds	Nightlight, one thermal infrared (10 um)	1992-2013	No	Yes
NPP-VIIRS	15 arc seconds	Nightlight, 21 additional bands spanning 0.4 to 13 um	2012-present	Yes	No

Recent studies showed the progress of applying the new NPP-VIIRS data in carbon emission modeling (Cui et al., 2019; Ou et al., 2015a; Zhang et al., 2020). The comparative findings demonstrate that the NPP-VIIRS data can more precisely demonstrate the spatial variations of residential carbon emissions than the DMSP-OLS. The emissions modeled by the NPP-VIIRS have larger values and more detailed spatial patterns in built-up areas, thus the NPP-VIIRS data are more effective in enhancing the knowledge of the regional differences of carbon emissions and serving as a benchmark for decomposing the low-carbon goals into each subunit (Ou et al., 2015a; Zhao et al., 2018). Moreover, some modeling studies have integrated the NPP-VIIRS and the DMSP-OLS to expand the time span of the NPP-VIIRS (Lv et al., 2020; Zhao et al., 2019). These studies have demonstrated the feasibility and superiority of using the NPP-VIIRS to model carbon emissions, as well as the possibility to facilitate other scientific applications that have adopted the DMSP-OLS product.

In particular, some studies employed adjusted nighttime light indexes to eliminate the oversaturation effect of DMSP-OLS by involving vegetation information. Zhang et al. (2013) established the vegetation-adjusted NTL urban index (VANUI) by integrating the Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) products with the NTL data (Equation 1). The VANUI is easy to compute and can characterize changes in light density within urban areas. Meng et al. (2017) applied an improved VANUI to model the carbon emissions in China by incorporating NTL, MODIS NDVI, population density, and a Water-masked map from ESRI. The findings showed that the proposed improved index can better reveal the spatial patterns of human activities. The improved index is also helpful to decrease the modeling error of carbon emissions across different cities and differentiate the heterogeneity in emissions within a city. The root mean square error (RMSE) of the improved VANUI model is 5.9% lower than that of the original VANUI model.

$$\mathrm{VANUI} = (1 - (\mathrm{NDVI}))(\mathrm{NTL}) \qquad \text{Equation 1}$$

However, the VANUI, which is calculated based on NDVI, is not effective to capture the intra-urban change in fast-growing cities because NDVI is less sensitive in built-up areas with low vegetation coverage (Huete et al., 2002). At the same time, VANUI is still affected by the blooming problem of the DMSP-OLS product.

Further to the development of VANUI, the enhanced vegetation index (EVI) adjusted nighttime light index (EANTLI) has been developed (Zhuo et al., 2015). The index is computed by integrating the MODIS EVI and the DMSP-OLS (Equation 2). Since the EVI is capable of offering information that is negatively and closely correlated with features of the urban areas (Liu, X. et al., 2015), it has been confirmed that the index can be easily used to deal with saturation, identifying the changes of the NTL brightness value in the built-up areas. Therefore, it is very helpful for analyzing the urban structure and modeling carbon emissions (Zhuo et al., 2015). Moreover, the accuracy assessment based on the statistical carbon emission at the city level also shows that EANTLI is not only suitable and effective for modeling carbon emissions in lighting areas, but also in non-lighting areas.

$$\mathrm{EANTLI} = \begin{cases} \dfrac{1 + (NTL_{norm} - EVI)}{1 - (NTL_{norm} - EVI)} \times NTL, & \mathrm{EVI} > 0.01 \\ 0, & \mathrm{EVI} \leq 0.01 \end{cases} \qquad \text{Equation 2}$$

where NTL represents the digital number of the NTL data, NTL_{norm} means the normalization of NTL, and EVI refers to the EVI data retrieved from MODIS data.

Liu et al. (2018) combined the EANTLI with LandScan population data to map the urban carbon emissions in China. Zhuo et al. (2015) and Zhao et al. (2018) compared

the accuracies of the VANUI and the EANTLI in mapping carbon emissions. Their results demonstrated that the EANTLI is capable of detecting significantly more spatial details within built-up areas than VANUI. Also, the EANTLI is more similar to the calibrated NTL compared to VANUI. Finally, the EANTLI more accurately predicted the consumption of electricity for 166 Chinese prefecture-level cities and the R-squared value increased by 11.8% in the linear regression model between the predicted electricity power use and the statistical carbon emission (Zhuo et al., 2015).

3.2.2 regression models

There are generally two main procedures for downscaling statistical carbon emissions at the jurisdiction level. The first procedure is data preparation, including the calculation of statistical carbon emissions at the administrative level from energy reports, the calibration of the NTL data, and the extraction of urban areas. Secondly, by establishing the relationship between statistical carbon emissions and NTL, an emission value is assigned to each pixel of NTL on this basis, and integrated into the urban scale.

Simple regression methods can be utilized to build the linear relationship between NTL data carbon emissions. For instance, Meng et al. (2014) predicted the urban carbon emissions for China based on the statistical relationship between the DMSP-OLS product and provincial carbon emissions. Lu and Liu (2014) adopted the DMSP-OLS product to acquire an index to represent human activities and verified the assumption that counties with close carbon emissions would cluster in space. Zhao et al. (2020) used a linear regression model to map the carbon emissions from 2000 to 2017 and explored the relationship between CO_2 emissions and nighttime land surface temperature in the Yangtze River Delta (YRD) Region.

The reliability of the simple linear relationship between NTL and statistical emissions can be weakened by the lack of data verification (Wang, S. et al., 2014). Besides, only the spatial or temporal relationship can be explored by linear regression models, which may cause deviations in the modeling of carbon emissions in both space and time dimensions. Panel data analysis can link the statistical emissions and NTL in spatiotemporal dimensions simultaneously. Therefore, panel data models have already been used for carbon emissions estimation (Cui et al., 2019; Han et al., 2018; Shi et al., 2016; Wang and Liu, 2017; Zhang et al., 2021).

Moreover, the geographical and temporally weighted regression (GTWR) model has also been used to build the relationship between statistical carbon emissions and NTL data due to its considerations of spatial and temporal heterogeneity of CO_2 emissions. Using the GTWR and NPP-VIIRS, Zhang et al. (2020) mapped CO_2 emissions from

coal boilers, thermal power plants, and natural gas boilers in 15 northern provinces from 2012 to 2017 with a resolution of 5 km × 5 km.

3.3 bottom-up method

Bottom-up methods to model urban carbon emissions generally integrate emissions at a point or sectoral level and then allocate the emissions into the designated spatial unit (Cai et al., 2018b). The relevant studies are summarized in Table 3.

There are some open bottom-up inventories at the facility level, such as the China Cement Emission database (Liu et al., 2021) and China coal-fired Power plant Emissions Database (Liu, F. et al., 2015). There are also other studies to develop carbon emission maps using bottom-up approaches. Zhang et al. (2014) proposed an analysis framework for carbon emissions estimation based on land use type and examined the spatial variations of carbon metabolism in Beijing. Household and personal surveys have also been applied to plot the carbon emissions (Rong et al., 2020; Yang et al., 2015). Wu et al. (2018) established a database for energy use intensity (EUI) from the Shanghai building energy efficiency monitoring platform for each building function and mapped the emissions of Shanghai based on the EUI and the building function. Zhang, R. et al. (2018) deployed a traffic allocation model to simulate traffic in road networks through a gasoline consumption function, i.e. the User Equilibrium (UE) in the JICA-STRADA 35 platform (Tscharaktschiew and Hirte, 2010). With the advances in big data development, taxi GPS trajectory data from taxi companies have been adopted to map high-resolution taxi emissions by daily travel (Luo et al., 2017; Xia et al., 2020; Zhang, J. et al., 2018; Zhao et al., 2017).

Table 3 Literature on the data used in the bottom-up methods

Study area	Resolution	Transportation sector	Building sector	Industrial data	Reference
Shanghai	point	1054 household surveys (transport mode, petrol consumption)	1054 household surveys (energy use at home and demographic characteristics)	No data	Yang et al. (2015)
Kaifeng	point	No data	3895 household surveys (energy use features, cognition and preferences and demographic characteristics)	No data	Rong et al. (2020)
Beijing	500 m	No data	Empirical conversion coefficients from IPCC for commercial and residential land use type; land-use maps of Beijing in the government databases	Empirical conversion coefficients from IPCC for industrial land use type; land-use maps of Beijing in the government databases	Zhang et al. (2014)
Shandong	500 m	Fleet size, annual average vehicle-traveled distance, vehicle age	No data	No data	Sun et al. (2016)
Shanghai	100 m	No data	Building energy use from the 2016 Shanghai Statistical Yearbook and public building energy efficiency monitoring platform; building use predicted from building morphology and Point of Interest (POI) of the OpenStreetMaps	Shanghai Statistical Yearbook	Wu et al. (2018)

Changzhou	Line (road link)	Origin-Destination data from the survey of the individual trip in Changzhou	No data	No data	Zhang, R. et al. (2018)
Changzhou	500 m	Taxi GPS trajectory data for 10,000 taxis, household travel questionnaires, POI data	No data	No data	Xia et al. (2020)
seven selected districts in Wuhan	500 m	Taxi GPS trajectory dataset for 6500 taxis from a taxi company, travel questionnaires from Center for Social Survey Research of Wuhan University, POI data	No data	No data	Zhao et al. (2017)
Beijing	100 m	Taxi GPS trajectory dataset	No data	No data	Zhang, J. et al. (2018)
Shanghai	100 m	Taxi GPS trajectory dataset for 13,675 taxis from a taxi company	No data	No data	Luo et al. (2017)

3.4 carbon satellite observations

Employing carbon satellites to model urban carbon emissions is another relatively new approach. Carbon satellites are the key data source for observing regional and global CO_2 distributions (Crisp and Miller, 2010; Yoshida et al., 2011). The CO_2 concentration obtained by satellite observations has the advantages of global coverage, frequent temporal resolution, and uniform observation, thus the spatiotemporal changes in atmospheric CO_2 concentration can be reflected (Yang et al., 2019). At present, the satellites with public access include the Scanning Imaging Absorption Monitoring Spectrometer for Atmospheric Chartography (SCIAMACHY) from Europe, Orbiting Carbon Observatory 2 (OCO-2) and OCO-3 from the USA, the Greenhouse Gases Observing SATellite (GOSAT) and GOSAT-2 from Japan, and the Chinese carbon dioxide observation satellite (TanSat) from China (Table 4).

The column-average dry air mole fraction of CO_2 (XCO_2) enhancements from the satellite observations are positively correlated with fossil fuel carbon emissions from human activities. Therefore, the XCO_2 can be adopted to quantitatively predict anthropogenic CO_2 emissions in a data-driven way (Yang et al., 2019). For example, Hakkarainen et al. (2016) employed the XCO2 obtained from the OCO-2 to develop the first direct observation of anthropogenic CO2 for the regions with high pollution including East Asia, central Europe, and the eastern USA. Yang et al. (2019) developed a method for modeling fossil fuel CO2 emissions in China by an artificial neural network based on the XCO2 generated from GOSAT. In order to estimate the CO_2 levels in China, Wang et al. (2011) used the level 3 products of XCO_2 obtained from the SCIAMACHY with a spatial resolution of 0.5◦, land cover maps, and emission inventories of the Regional emission inventory in Asia (REAS) dataset. Yang et al. (2018) used the observations from the TanSat satellite to generate the first Tansat global XCO_2 maps.

Table 4. Comparison of the carbon satellites

Satellite	**Operator**	**Spatial resolution**	**Temporal resolution**	**Launch year**
SCIAMACHY	ESA	30 × 60 km	Every 6 days	2002
GOSAT	JAXA, MOE, and NIES	10.5 km	Every 3 days	2009
GOSAT-2	JAXA, MOE, and NIES	9.7 km	Every 6 days	2018
OCO-2	NASA	1.29 × 2.25km	Every 16 days	2014
OCO-3*	NASA	1.29 × 2.25km	Every 16 days	2019
TanSAT	CAS	1 ×2 km, 2 ×2 km	Every 16 days	2016

** https://disc.gsfc.nasa.gov/datasets?keywords=OCO-3*

ESA (Envisat, a European Space Agency), JAXA (Japanese Aerospace Exploration Agency), MOE (the Japanese Ministry of the Environment), NIES (the National Institute for Environmental Studies), NASA (The National Aeronautics and Space Administration) and CAS (Chinese Academy of Sciences).

3.5 hybrid method

Hybrid approaches involving both bottom-up and top-down methods have been implemented to retain the accuracy of the bottom-up method and the efficiency of the top-down method. The central government and planning departments in China have produced some national spatial inventories of carbon emission using hybrid methods with open access. For example, the China High Resolution Emission Database (CHRED) was created by the Chinese Academy for Environmental Planning (Cai et al., 2018b). Among all the available emission data sources in China, the CHRED has the finest spatial resolution so far (1 km). The dataset was created primarily based on point emission sources from the industrial sector and complementary socio-economic information of Mainland China (Figure 1). Industrial emissions were modeled by the bottom-up approach, taking advantage of the point emission sources at the facility level containing approximately 1.5 million enterprises from the First China Pollution Source Census (FCPSC) dataset. The FCPSC may be China's first comprehensive census of energy use at the national level. The FCPSC contains detailed information on fossil fuel consumption and industry location at the facility level. It also includes district/county-level residential energy consumption. Emissions from the transport, services, and agricultural sectors of the CHRED were disaggregated from statistical data using social-economic and urban land use data using top-down approaches. Statistical emissions from the residential and agricultural sectors at the province level were downscaled equally to the grid of the corresponding land use type generated from remote sensing imaging and population data. Finally, the emissions from the different sectors were synthesized into one database. In addition, Wang, J. et al. (2014) constructed a high spatial-resolution (10 km) map of carbon emissions for China, with emissions from the industrial and residential sectors also generated from the FCPSC dataset. Hao (2015) mapped the industrial, enterprise and residential emissions from the FCPSC dataset, and used weights of road type, population, and land use as proxy data to disaggregate transportation and agriculture emissions.

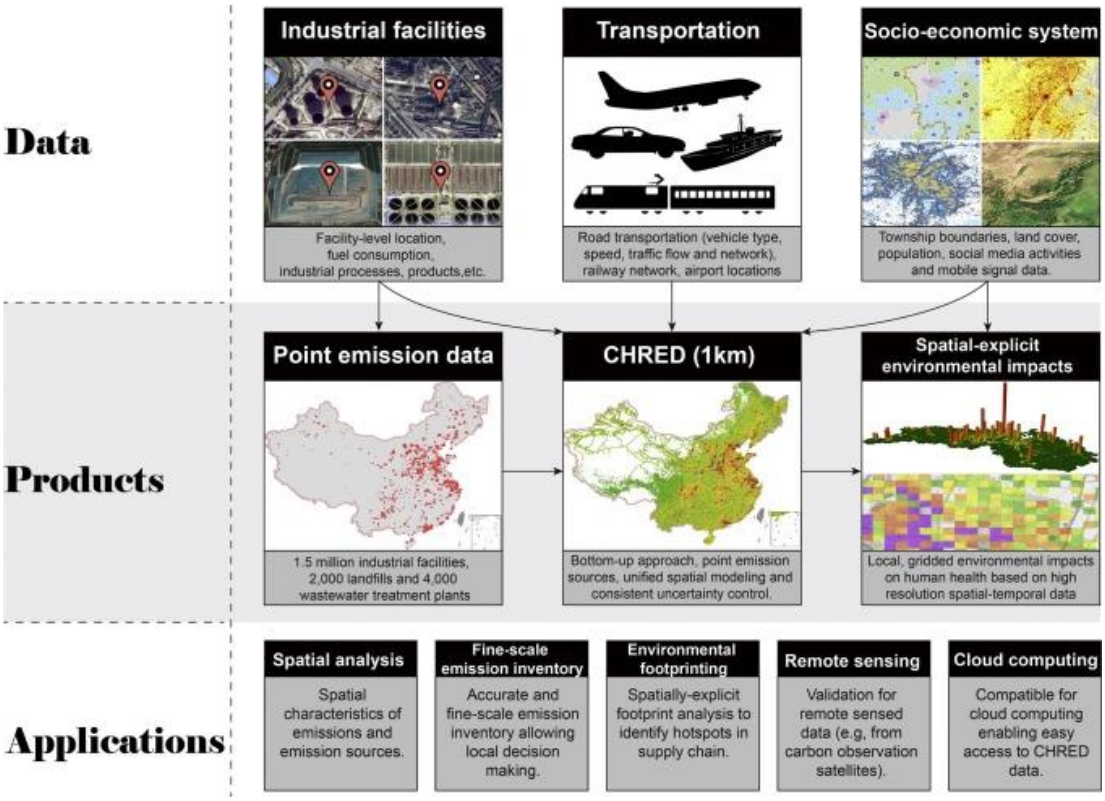


Figure 1 The framework of the CHRED (Cai et al., 2018b)

The standardized CHRED framework has been used for cities and regions for more precise and localized results. Cai and Wang (2013) and Cai and Zhang (2014) established a carbon emission inventory in Tianjin and Shanghai at a 1 km resolution and discussed the CO_2 emissions within different spatial boundaries. In addition, the emissions within four spatial boundaries were compared according to the carbon emission maps of Tianjin (Cai and Wang, 2013). Cai used the same framework to model the carbon emissions for Chongqing (Cai, 2014), Shanghai (Cai and Zhang, 2014), and cities in the YRD region (Cai and Wang, 2015), Jing-Jin-Ji (Beijing-Tianjin-Hebei) region (Cai et al., 2018a), and further improved the methodology by utilizing localized datasets at finer spatial resolutions.

Tsinghua University developed The Multi-resolution Emission Inventory for China (MEIC, http://meicmodel.org/) (Li et al., 2017; Zheng, B. et al., 2018). The dataset contains the spatial distribution of ten air pollutants and CO_2 in mainland China with the finest grid of 0.25° × 0.25°. The inventory has 5 sectors, including power, industry, residence, transportation, and agriculture. The carbon emissions from power, cement, and steel industries are generated from two bottom-up inventories, i.e., the China Cement Emission database (Liu et al., 2021) and Global Power Emissions Database (Tong et al., 2018). Important proxy data in the top-down method for downscaling emissions include population, roads, and power plants.

Apart from using the standardized framework, localized hybrid methods have also been applied in many cities. For instance, Dai et al. (2020) produced the carbon emission database for Jinjiang city, China with a spatial resolution of 30 m and 500 m using a hybrid approach. The industrial emissions were calculated at the point level by a bottom-up method. Emissions in other sectors were allocated to the spatial grid based on spatial proxies such as population map, land use, and NTL data using top-down approaches. Similar studies have been conducted for Changxing (Liu et al., 2020) and Shanghai (Zhu et al., 2019) with industrial emissions at point level, road emissions at street level, and building emissions at the area level. Zhao et al. (2012) used the bottom-up method to estimate point-level industrial emissions and employed GDP and population to downscale provincial emissions in China at the resolution of 0.25° × 0.25°. Furthermore, Cai et al. (2020) adopted the hybrid method for developing the spatial inventory in Hong Kong with a resolution of 100 m. Industrial and airport emissions were modeled using the bottom-up method. Urban form and traffic flow were used as proxies for building and traffic emissions respectively in the top-down approach.

3.6 impacts of urban form on carbon emissions

3.6.1 impacts of urban morphology

It is found that the urban complexity, urban compactness, and urban development patterns are the major indicators to characterize the urban morphology. The urban complexity represents the extent of the irregularity of the perimeter of the land lot, and urban compactness reflects the degree of dispersion or sparseness of the land lot (Makido et al., 2012). Urban development patterns include different urban development strategies such as the mononuclear pattern or multiple-nuclei pattern (Ou et al., 2019).

Several studies revealed that the increase in urban complexity has an impact on increasing carbon emissions (Fang et al., 2015; Ou et al., 2013; Ou et al., 2019; Shi et al., 2020; Shu et al., 2018; Wang et al., 2019). Results from quite a large number of studies showed the compact urban setting can lead to low carbon emissions and increase energy efficiency since the transport energy consumption can be reduced (Chen et al., 2008; Ou et al., 2013; Wang, M. et al., 2017; Wang, S. et al., 2017; Wang et al., 2019). Meanwhile, there are also studies having negative opinions on urban compaction since it will increase residential energy consumption (Miao, 2017; Sha et al., 2020; Ye et al., 2015). Li et al. (2018) pointed out that the urban density at the neighborhood level varies for different types of dwelling units.

There are also some debates on the effect of urbanization patterns on carbon emissions. Some studies found that polycentric urbanization can improve CO_2 emission efficiency (Ou et al., 2013; Sha et al., 2020). Therefore, they suggested urban development patterns in a decentralized and polycentric way in order to reduce CO_2 emissions. However, Wang, Y. et al. (2014) pointed out that the transformation to a scattered and polycentric urban form in Beijing could increase driving

distances, which could cause a significant increase in transport emissions. Also, Wang, S. et al. (2017) believed that urban development in a multiple-nuclei pattern at the metropolitan level may not effectively mitigate carbon emissions. A recent study revealed that the impact of urban development patterns varies for cities under different development stages (Ou et al., 2019).

3.6.2 impacts of urban land use/land cover

The interplay between carbon emissions and urban land use has also been investigated by previous studies. Zhang, R. et al. (2018) explored the role of land use planning in reducing carbon emissions from the transport sector. The construction land use and landscape fragmentation can increase the carbon emissions at a lower proportion and reduce the emissions at a larger proportion. Residential and commercial land uses can increase carbon emissions, while green space can decrease carbon emissions. However, the impact of industrial land use was found to be not significant in this study. Xia et al. (2020) found that land use diversity can decrease carbon emissions, while urban residential density has a positive impact on increasing carbon emissions in Hangzhou. Higher accessibility to water bodies and green space is also associated with lower carbon emissions (Ye et al., 2015). Ying et al. (2008) indicated there are significant differences in carbon emissions of different land use patterns, in which the construction land and cultivated land are the two major carbon sources, while forest land and grassland are related to low carbon emissions. Land use change is also found to be associated with high emissions (Zhao et al., 2021). Guan et al. (2019) investigated the low carbon transport (LCT) in China and concluded that only the land use diversity may not be capable of changing the LCT mode choice for Chinese cities. Liu et al. (2016) concluded that residents living in a neighborhood with higher land use mix, public transit accessibility, and more pedestrian-friendly street design tend to travel in an LCT manner. Shen et al. (2020) suggested mitigating transport emissions by improving parking availability rather than land use reconstruction.

4 Discussions

4.1 cross-comparison of the methods

The characters of the three methods are summarized and compared in this section (Table 5). The top-down method using NTL data is simple to compute and conduct. Therefore, the approach can be applied to cities or regions without detailed emission data. Also, the method can be easily and efficiently applied to large areas as NTL data have global coverage. Therefore, the method has been widely applied at the regional and national scales for China. The accuracy of the method can achieve a medium level of 70% to 90%. However, this method cannot perform well in developing countries since the relationship between the NTL pixel value and carbon emissions is less significant in developing countries than in developed countries (Doll et al., 2000). This may affect the accuracy of the top-down method in modeling the carbon emissions in developing countries with rapid urbanization and industrialization like China. Secondly, previous studies found out that

the top-down method can cause almost 50% per pixel error rate from DMSP-OLS data, and these errors are geographically correlated (Rayner et al., 2010). Thirdly, the top-down approach using NTL is likely to underestimate emissions from transportation and industrial sectors because the NTL data generally reflect socioeconomic characteristics instead of fossil fuel combustion during the night, which may not accurately predict the human activities relevant to transport and industrial process (Ghosh et al., 2010). Moreover, a higher brightness value in the NTL data does not always indicate higher carbon emissions since electricity generation and electricity consumption often take place in different areas (Meng et al., 2014). Therefore, the data quality and the existing workflow of the top-down model still need to be improved to achieve more accurate and comprehensive estimates of carbon emissions.

Through requiring more detailed data, the bottom-up method usually provides the most accurate results. In particular, the bottom-up method is mainly implemented by government authorities because it is suitable for local-scale assessment and therefore favored by governors at the city, district, community, or household levels. There are also limitations of the method. Firstly, it is difficult to conduct data collection since it costs extensive time, labor force, and material resources. This method requires accurate and detailed data about energy consumption, emission sources, and socioeconomic information, so it cannot be used in cities or regions without such data, especially for developing countries and regions where such data set is either not publicly available or under development (Zheng, S. et al., 2018). Second, it is difficult to collect energy, emission, and socioeconomic data with the same time scale and consistent status. As a consequence, the applicability and comparability of the method are limited and it can be challenging to develop a generic way to model the spatial patterns of the carbon emissions across different cities (Jing et al., 2018).

The carbon satellite approach is capable of developing a comprehensive understanding of urban carbon emissions with global coverage and frequent temporal resolution. Consistent satellite observations can be adopted to identify the carbon sources and sinks in both space and time dimensions. This method is likely to enhance the current emission inventories with the further development of satellite products. The major shortcoming of this method is the low spatial resolution, generally greater than 10 km, depending on the sensor. Therefore, it is mostly used at the global or national levels instead of the city scale at present due to the restrictions in resolution and accuracy. Also, it is difficult to identify the variations of the magnitude of the emissions in certain urban areas from the carbon satellite system, as the CO_2 signal from the main urban cores can be spread out and deviated from the emission sources, which may result from the low resolution as well as atmospheric transmission, mixing and retention (Ou et al., 2015a). With the improvement of spatial resolution of future carbon satellites, this method can be better exploited in urban carbon emission modeling.

Table 5. Cross-comparison of the three methods

Methods	Top-down method from nightlights	Bottom-up method	Carbon satellite observation
Spatial coverage	Global coverage	Usually local coverage	Global coverage
Finest spatial resolution	500 m	Point	1 km
Temporal resolution	Monthly or annual	Usually a single year	Weekly, monthly, Or annual
Accessibility	Freely available	Usually requiring non-public data	Freely available
Accuracy	Medium accuracy (70% to 90%)	Usually most accurate	Low accuracy
Applications	Regional, national-scale studies	Local estimation at the city, district, community or household levels	National-scale studies

4.2 policy implications

In order to recognize the importance of cities in improving energy efficiency and mitigating carbon emissions, the Chinese government aimed to encourage carbon neutrality strategies and promoted a low-carbon urban development demonstration project in 5 pilot provinces and cities in 2010 (National Development and Reform Commission of China, 2010).

The understanding of the impact of urban form can therefore be useful in formulating the low-carbon policies for Chinese cities. Fundamentally, a spatial inventory of CO_2 emission should be established for each city as a reference for the investigations on the impact of urban form. The results from the literature generally favor a regular and continuous urban form for reducing CO_2 emissions. Also, the accessibility to greenery and water bodies can help reduce carbon emissions in urban areas. However, there is yet to be a clear conclusion on the impact of urban compaction, polycentric spatial development, commercial, and industrial land use. Their influences can vary significantly among different cities. So, decision-makers should take serious considerations of these factors which deserve a detailed investigation and sectoral scrutiny. The studies also highlighted the importance of balancing the impacts of urban form and the feasibility of optimizing urban form. China already has high population densities in urban areas, therefore increasing urban compactness by further densifying the urban population to decrease carbon emissions may not always be feasible in Chinese cities. Land-use control may reduce emissions in some cities, but it

usually brings higher costs. However, if policies are executed properly with cooperation across cities, or induce significant co-benefits, they could be an effective mitigation solution (Leibowicz, 2017).

4.3 implications from other countries

Urban forms are found to influence the spatial distribution of carbon emissions; urban form data is therefore essential for constructing a more accurate spatial emission inventory. Some spatial modeling studies in other countries have already taken urban form data into account. For example, the United States developed the Vulcan dataset with a 0.1-degree resolution (http://vulcan.project.asu.edu/research.php.). Carbon emissions from the various sectors including commercial, industrial, and residential, as well as road and non-road transport were modeled by the Vulcan dataset (Gurney et al., 2009). The Vulcan dataset was developed by a bottom-up approach using seven major datasets containing the road networks, spatial information of point emission sources, the floor and areas of buildings, etc. (Gurney et al., 2009). It is generally regarded as the most precise carbon emission inventory (Andres et al., 2012).

China can learn from the low-carbon experience of Japan for its carbon emission mitigation for the following reasons(Ouyang and Lin, 2017). First, the two countries shared similar economic development experiences (Minami, 2016). Secondly, Japan is recognized as the leading country for energy conservation and emission control in advance of other countries in the world (Honma and Hu, 2008; Ouyang and Lin, 2017). Scholars in Japan have developed accurate estimations for urban carbon emissions. Sharifi et al. (2018) proposed a standardized framework to obtain a synthetical understanding of urban carbon emissions (Figure 2). The framework synthesized emissions from the building and transport sectors. The annual carbon emissions of a building can be determined by the EUI and the building attributes, such as building function and building floor. For the transport sector, carbon emissions were determined by the energy consumption for each transport type and the corresponding emission factors. This framework has already been adopted to map the urban carbon emissions in Shanghai (Wu et al., 2018), and Tokyo (Sharifi et al., 2018).

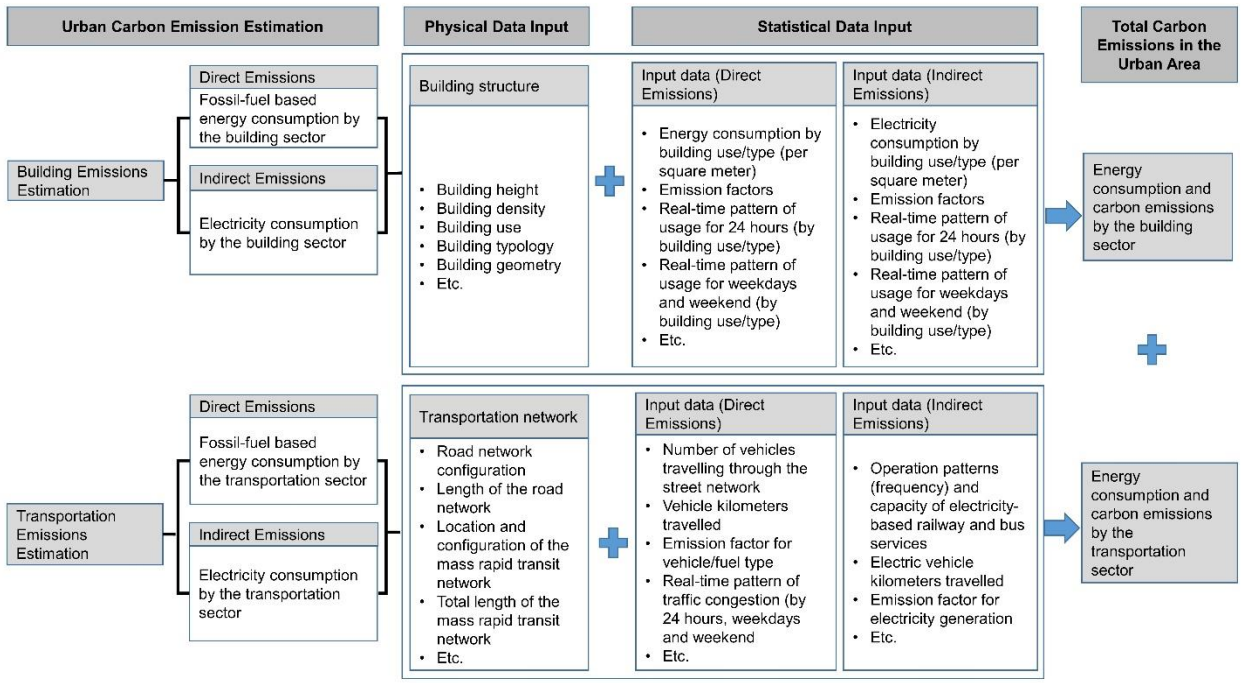


Figure 2 the framework for modeling urban carbon emissions proposed by Sharifi et al. (2018)

The modeling methods in these countries involved high-resolution urban form data such as the building footprint and location of the point sources to accurately detect the spatial patterns of the carbon emissions in urban areas. Consequently, the location and the emissions from the various sources, such as power plants, road networks can be retained. However, most studies in China did not adopt urban form data due to data availability, and only one study used urban form data (Cai et al., 2020). The accuracy of carbon emission data in China can be improved by incorporating urban form as input.

4.4 future research directions

With the development of urban data science, several future directions of the development of the spatial inventory can be identified from this review:

Firstly, the spatial modeling studies in China generally used land use data, NTL or population as the elementary emission sources, ignoring the impacts of urban form. With the development of urban form extraction techniques (Ren et al., 2019), further work involving high-quality urban form data in the modeling process is necessary to obtain more accurate spatial patterns of urban carbon emission for Chinese cities. Also, adopting urban form data in the modeling can support researchers, urban planners, and policymakers to have in-depth knowledge of the impact of the urban form and devise corresponding planning strategies.

Besides, previous data often have a spatial resolution greater than 1 km. Inventories with the finer spatial resolution are required for more accurate identification of emission hotspots and targeted planning strategies.

Furthermore, the IPCC method and traffic models are mostly used in the bottom-up method. Simple linear regression is widely adopted in the top-down approach. Panel data model and GTWR have also been implemented to account for spatial and temporal heterogeneity. Other machine learning algorithms such as random forest and artificial neural networks, can explore non-linear relationships with higher precision and are anticipated to increase the modeling accuracy in further studies.

Finally, in the building sector, land use, POI, and household survey are frequently used for spatial analysis. For the transportation sector, road network, taxi GPS data, vehicle information are the commonly used spatial data. Industry locations and point-level energy consumption are generally used for mapping industrial emissions. Nevertheless, the industry locations and energy activities, taxi GPS data, vehicle information, and household surveys are generally unavailable for most cities in China. The lack of a generally applicable method using open data impedes the consistency of carbon emission estimates and mitigation strategies across different cities. Therefore, an open-data based standardized methodology is essential for collaborative efforts in carbon emission assessment and mitigation strategies for global cities.

5. Conclusions

In this study, the spatial modeling of urban carbon emissions and the impact of urban form in China are systematically reviewed and analyzed. The currently available datasets and methods for spatial modeling are summarized. The common methods include top-down approaches using NTL, bottom-up analyses, carbon satellite observations, and hybrid methods.

The strengths and weaknesses of the methods were compared to explore the future needs and trends in the development of spatial models. The top-down method based on the NTL can be implemented to predict the spatial variations of the regional and national carbon emissions using openly available data sources, but the accuracy of the product can be influenced by the data quality of the NTL and the underestimation of the emissions from transport and industrial sector. The bottom-up method has generally been conducted locally by government authorities or planning departments and has been able to secure accurate carbon emission data. However, the universal application of this method is limited by data availability. The carbon satellite method is relatively new. It is simple to implement but its application in urban areas is still limited due to the coarse spatial resolution.

The urban forms, including urban morphology and land use, are found to affect carbon emissions. In terms of urban morphology, the increase in the urban complexity can contribute to higher carbon

emissions, while there are still some discussions on the impacts of urban compaction and the choice of urban spatial development pattern. The impact of the proportions of land use types varies in cities under different development stages and sizes. Therefore, the impact of the urban form should be analyzed for individual cities for a specific and targeted understanding. The policymakers and urban planners should seriously consider these urban form indicators and develop corresponding urban design policies in a sensible way.

However, based on the literature, it is found that most studies in China do not consider urban form data. This may greatly impact the urban carbon emission estimation and management since a complex urban morphology and high-density urban context can be found in most Chinese cities. Moreover, the spatial inventories of urban carbon emission in China generally have a low spatial resolution over 1 km. Urban carbon emission models with a finer resolution are needed for more accurate urban studies at the neighborhood and building scales. With newly developed urban morphology extraction technology and machine learning techniques, more accurate inventories of urban carbon emissions at higher spatial resolutions can be developed by incorporating detailed data on urban form. Open and high-quality urban form data is also helpful to the development of a generic method to conduct high-resolution urban carbon emission modeling for global cities.

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