Developing a High-resolution Emission Inventory Tool for Low-Carbon City Management Using Hybrid Method – A Pilot Test in High-density Hong Kong

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Highlights

- A hybrid method was developed to model urban carbon emission at high-resolution.
- Open urban form data of building attributes and traffic flow were utilized.
- The hybrid method was demonstrated in high-density Hong Kong.
- Annual carbon emission maps were generated for the building and transport sectors.
- Validation results show the robustness and broad applicability of the method.

Abstract

Energy is one of the crucial elements in creating resilience in cities. Global cities produce more than 70% of the world's carbon emissions from energy activities and thus play an important role in changing climate and causing environmental problems. The spatial modelling of urban carbon emissions can serve as the basis for carbon emissions mitigation. Building attributes are the key energy demand indicators and significant in constructing the emission inventory, but they are often not accounted for in the modelling process due to data availability. Therefore, this study aims to develop a tool for modelling a high-resolution emission inventory using open urban form data and demonstrate it for Hong Kong. This tool modelled the urban carbon emissions for building and transport sectors using a hybrid method involving both bottom-up and top-down approach. Open urban data including building attributes and traffic flow were extracted as model input data. The urban carbon emissions were modelled for Hong Kong at 100m spatial resolution for different sectors and integrated in Tertiary Planning Unit. Validation results show that the method has reasonably represented both the total emissions and the spatial pattern of urban carbon emissions of Hong Kong. The spatial distribution of carbon emissions of Hong Kong can provide reference information for low-carbon city management for other high-density cities. The method shows the potentially broad applicability, therefore contributing to the global collaborative effort in the mitigation of carbon emissions.

Keywords: high-resolution emission inventory, urban carbon emissions, low-carbon city, urban form, open data.

1. INTRODUCTION

Climate change has caused a series of effects on Earth, such as rising temperatures and sea levels [1]. The anthropogenic climate change primarily results from the combustion of fossil fuels, which produce greenhouse gas (GHG) emissions. The Intergovernmental Panel on Climate Change (IPCC) further stressed that carbon dioxide (CO2) is the most important anthropogenic GHG in 2007 [2]. Energy is one of the crucial elements in creating resilience in cities because it is indispensable in sustaining citizens, diverse urban functions, industry and the overall economic growth of cities [3]. Cities account for about 64 percent of global primary energy use and produce over 70 percent of carbon emissions from energy activities [1, 4]. Thus, cities are the main targets for reducing carbon emissions. The United Nations estimate that the major increase of the global population will happen in cities from 2012 to 2050 [5]. World carbon emissions are expected to increase due to continuous urbanization.

Urban carbon emissions inventories can provide the basis for reducing carbon emissions and low-carbon development [6]. However, national or citywide estimations of carbon emissions are still the major source for informing the policymaking process, which is insufficient for the formation of the carbon emissions mitigation strategies [7]. Due to the absence of detailed information on spatial distributions, the spatial carbon emission dynamics within an administrative unit such as city or community boundary have not been clarified. Thus, it is necessary to develop finer-scale carbon emission inventories [7].

There are two commonly used methods for the spatial modelling of carbon emissions: 1) bottom-up analyses, a method that involves accurate emission data from sectoral energy consumption data [8] or point source carbon emission data [9]; 2) top-down models that distribute the carbon emissions of a large area to finer spatial unit based on certain proxy data and algorithms. The bottom-up method generally calculated the carbon emissions from the emission sources and can achieve the most accurate results [9, 10]. There are some open carbon emission products derived from the bottom-up method at global or national scale developed by government authorities or the planning departments, such as China High Resolution Emission Database (CHRED)[10] , Emission database for global atmospheric research (EDGAR) [11], Vulcan in the United States

[12]. Despite the good spatial coverage, these datasets have coarse spatial resolution larger than 1km which does not provide enough detailed information on the spatial patterns of carbon emissions within an administrative unit. Apart from these publicly available datasets at the national or the global scale, many urban carbon modelling studies have been conducted for individual cities to achieve more detailed and localized data to better inform the local low-carbon strategies [9, 13-15]. However, the workflows developed by the above studies cannot be widely applied to global cities due to the lack of detailed urban data. As a result, the comparability and applicability of these studies are limited since it is insufficient to estimate carbon emissions distribution for different cities [16].

The top-down method using proxy data to disaggregate the statistical carbon emissions to a certain spatial unit is based on the assumption that the proxy data is correlated with the carbon emissions related to the energy consumption of the same pixel [17]. The Nightlight (NTL) data population data, and land use data have been extensively used as the proxy data since they can provide a proper estimation of the human activities and socioeconomic conditions [18-22] [23]. The top-down method using these datasets can be easily implemented using openly available data for a large study area. However, the NTL data have saturation problem and cannot fully represent emissions from the transport and industrial sectors [24]. The population data cannot reflect some potential emissions in the commercial and industrial sectors without human settlement [25]. In addition, demographics cannot be used to pinpoint the exact location of emission sources since the census data usually indicate statistics at the administrative level or within a large spatial grid [25]. Also, the land use information can only provide a general characterization of the energy demand. Furthermore, the NTL, population data and land use data cannot reflect the variations of carbon emissions across different buildings. Meanwhile, building attributes are the key energy demand indicators and have also been applied in the top-down models [26]. In comparison with the nightlight and population data, the building information can reflect the energy performance in the business and industrial sectors and can highlight the location of the emission sources. Moreover, it is necessary to account for the building emissions since the building sectors are the major contributors to urban carbon emissions, especially for cities under rapid urbanization [27]. However, it is found that most studies on urban carbon emissions in China did not account for the building data due to data availability [28]. It is necessary to involve building data for a comprehensive and accurate top-down model of the spatial inventory of urban carbon emissions.

In sum, the previous spatial urban carbon emission inventories often have a coarse spatial resolution greater than 500m. Moreover, building information is found to have an impact on carbon emissions in urban areas [29-31]. A more accurate spatial pattern of urban carbon emissions can be modelled by incorporating building data. However, high-quality building data are often missing or not publicly available. Thus, there is still no universally applicable tool to model urban carbon emissions for different cities [32]. The openness and availability of urban carbon emissions data directly affect scientific research, the formation of low-carbon strategies and public participation in climate change mitigation [9, 33, 34].

Thus, it is necessary to develop a method for modelling carbon emissions spatial inventories at a finer resolution using publicly available urban form dataset. A consistent methodology using publicly available urban form data is essential for a better global collaborative effort in urban resilience and carbon emission mitigation. The spatial modelling of carbon emissions can serve as the foundation for the city 's carbon emission inventory and help to evaluate practical measures for the development of low-carbon cities to mitigate climate change. To fulfill the above needs, in this study, we develop an approach to model high-resolution carbon emission inventories and demonstrate the approach through implementation in Hong Kong, a city with high-density urban context and rising urban carbon emissions [35].

2. MATERIALS AND METHODS

2.1 Study area and data

Hong Kong is one of the most high-density cities in the world, with population of more than 7 million people and land area of 1,100 square kilometres [36]. With population growth and economic development, Hong Kong's energy consumption has increased significantly in the past few decades [37, 38]. Massive GHG was produced from energy usage in Hong Kong. In 2016, the GHG emissions were 41.09 million tons (Mt), of which about 90% were generated from energy activities [37]. From 1990 to 2013, per capita carbon emissions increased from 6.031 tons per capita to 7.225 tons per capita[35]. The impacts of climate change such as rising temperatures, frequent occurrences of extreme weather events and rising sea levels, have already affected Hong Kong [39]. The local government has set a target to reduce carbon intensity, i.e. the carbon emissions per unit GDP, to 65% -70% of the intensity in 2005 by 2030 for the development of the low-carbon city [38].

Moreover, high-rise buildings are compactly distributed in the urban areas in Hong Kong [40]. Compared with other emission sources in Hong Kong, buildings produce the largest amount of carbon emissions [39]. Therefore, it is necessary to mitigate the emissions from the buildings and account for building attributes in the spatial modelling of carbon emissions [39] .

Fig. 1. 18 districts of Hong Kong [36]

The study involves statistical data, spatial data, and emission parameters. Statistical data on fossil fuel consumption in Hong Kong including the Hong Kong energy statistic reports and Hong Kong energy end-use report only include energy consumption data counted at the city-level [37, 41]. The emission parameters were collected from IPCC [42]. The spatial data were adopted as the emission source and the proxy. There are mainly four types of transportation in Hong Kong: road network, Mass Transit Railway (MTR), civil aviation and marine. Therefore, the spatial data for the transport sector include road traffic flow and MTR route from the transportation department, civil aviation emissions from the civil aviation department, marine emissions [37]. The spatial data were all converted to raster format with 100m grid size. All the statistical and spatial data of 2016 were acquired for the consideration of data integrity.

Table 1. input data for the carbon emission model

Category	**name**	**source**	**Reference**
Statistical data	Hong Kong Energy Statistics	Census and Statistics Department	[41]
	Hong Kong energy end-use report	Electrical & Mechanical Services Department of Hong Kong (EMSD)	[37]
	Civil aviation emissions	Civil aviation department	[43]
Specific coefficients	CO2 Emission factors	IPCC	[42]
	Oxygenation efficiency	IPCC	[42]
	Net calorific Values	IPCC	[42]
spatial data	TPU boundary	Census and Statistics Department	https://www.census2011.gov.hk/en/tertiary-planning-units.html
	Traffic volume	Transportation department	[44]
	MTR route	MTR Corporation Limited	https://data.gov.hk/en-data/dataset/mtr-data-routes-fares-barrier-free-facilities/resource/31c59d00-11b0-4f67-b7c8-5721f0e4addf
	Ferry	Transportation department	https://data.gov.hk/en-data/dataset/hk-td-tis_14-routes-fares-xml/resource/521c1303-7318-4f0a-b60c-00a82269a1a1
	3D building	Google maps and AW3D30	[45]
	Building use	Data.gov.hk, Hong Kong Geodata store, Google maps, Amap	To be elaborated in table 2

2.2 Model description

In this study, a hybrid model involving both top-down and bottom-up methods was applied. Four sectors (transport, business, industry, and residence) will be accounted for in this model. We account for energy-related emissions including direct emissions from fossil fuels as well as indirect emissions from heating and power generation for each sector.

Firstly, the total emissions in each sector will be calculated following the IPCC guidelines (IPCC, 2006). The emissions that have specific spatial information and can be directly derived from openly available sources such as civil aviation, marine, will be modelled using the bottom-up method that directly assigns the emissions to the spatial grid of the emission source.

For emissions without detailed spatial information or publicly available sources, the spatial distribution of the carbon emissions can be modelled by the top-down method that distributes the statistical data to the emission source using proxy data. For building emissions including the business, industrial and residential sectors, buildings are considered as the emission source. Building attributes are identified as key energy performance indicators and form the basis of the building typology categorization [26]. Building attributes relevant to energy consumption include building use, as well as morphological attributes such as building volume, window, wall and roof areas [26]. The building volume density (BVD) represents the building morphology and provides an estimate of the space of the building [45]. The integration of BVD and building use can be used to assign the energy demand and thus is key in quantifying building carbon emissions. Therefore, building attributes including the building use and the BVD will be used as proxy data for allocating the emissions from buildings.

For the transport sector, the road network is regarded as the emission source. Traffic flow is the product of traffic density and velocity, so the traffic flow along the road network can reflect the patterns of traffic emissions [46]. Traffic flow will be modelled and be used as a proxy to calculate the transport emissions. Therefore, the emissions from each sector can be modelled and visualized on the Geographical Information System (GIS) platform. Finally, the statistical and spatial modelling results will be validated by other publicly available datasets.

Therefore, the model for creating the inventory contains six steps (Fig. 2): (1) preparation of input data; (2) accounting total carbon emissions by sector; (3) extraction of proxy data, including building use, building morphology and traffic flow; (4) disaggregation of the statistical data on carbon emissions to the level of emission sources; (5) visualization of results; (6) valuation of the results. The procedure will be illustrated with more details in section 2.3.

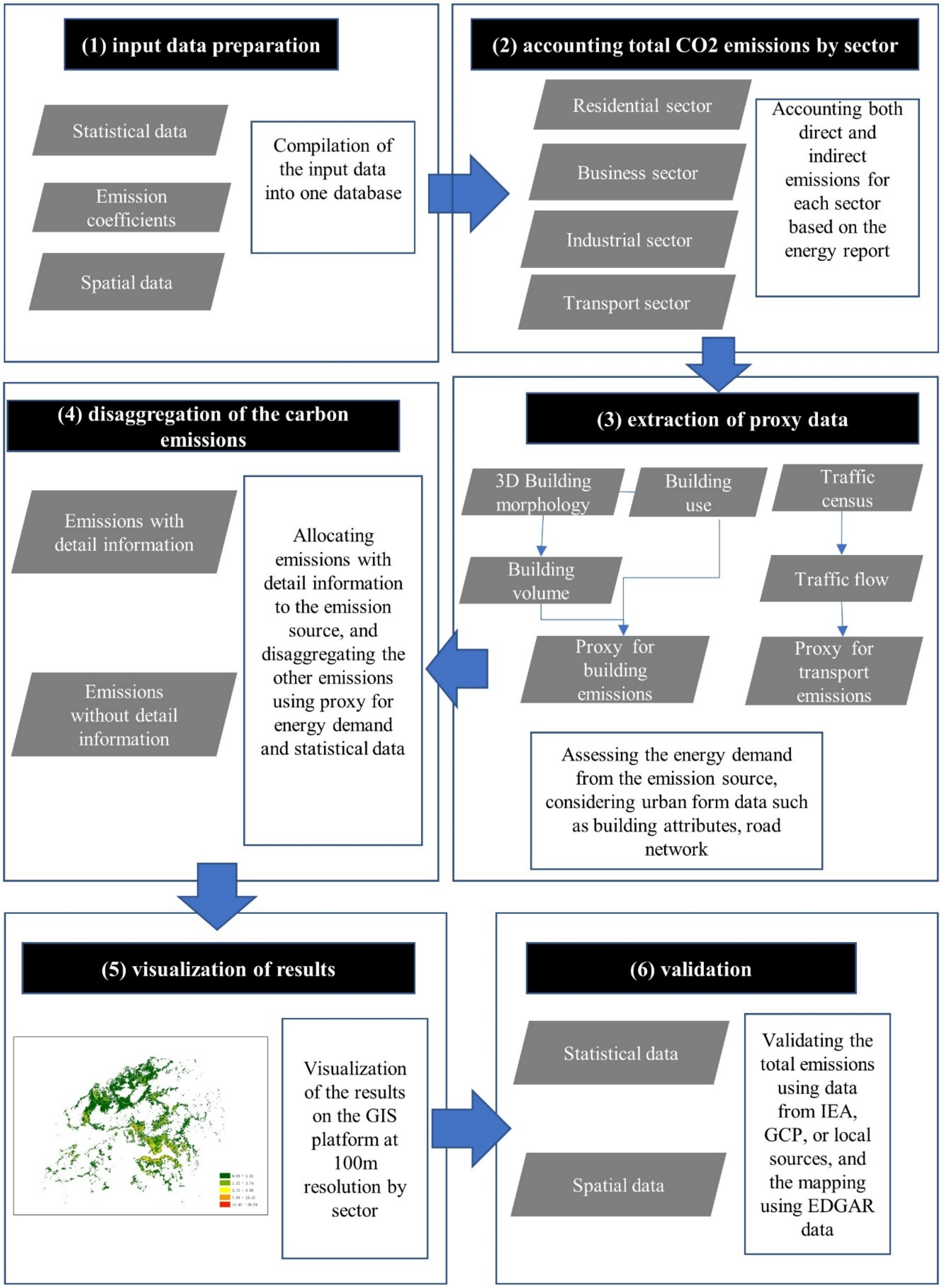


Fig. 2. the procedure for developing a spatial carbon inventory

2.3 Model application in Hong Kong

2.3.1 accounting total CO2 emissions by sector

The urban carbon emissions in Hong Kong include the emissions from the residential, business, industrial and transport sector. The emissions consist of direct emissions from fossil fuel combustion and indirect emissions from electricity generation. Hong Kong has a monsoon-influenced subtropical climate with warm winter, so the indirect emissions mainly come from electricity generation and the emissions from heat production can be neglected. Following the method in the IPCC report [42], the fossil fuel-related emissions were calculated as:

$$CE_{ij} = AD_{ij} \times NCV_j \times EF_j \times O_{ij} \quad (1)$$

where i presents different sectors, j shows fossil fuels type. CE_{ij} indicates the carbon emissions by sector i and fossil fuels type j. AD_{ij} denotes fossil fuel consumption. NCV, EF, and O are emission parameters of different fossil fuel types, which represent net caloric value, emission factors, and the oxygenation efficiency, respectively.

The indirect emissions were calculated based on primary energy input from Hong Kong Energy Statistics:

$$CE_i = CE \times \frac{E_i}{E} \qquad (2)$$

where CE is the total emissions from electricity generation, E_i represents the electricity consumption by sector i. Therefore, the carbon emissions for each sector can be acquired by aggregating the direct and indirect emissions.

2.3.2 spatial mapping of carbon emissions in the building sector

a). extraction of building use

The building attributes including the building use and building morphology will be extracted from open data to spatially model the urban carbon emissions in Hong Kong. According to the Hong Kong energy end-use report (Electrical & Mechanical Services Department of Hong Kong, 2018), there are statistics of energy consumption of different building uses in each sector, which is helpful to disaggregate the carbon emissions in each sector in more details. There are nine building use types from the report (Table 2). For the building use of the retail, office, accommodation, health and education, the name lists of the buildings have been provided by the local government (Data.gov.hk). The name lists were converted to the geographical coordinates using the geocoding function of the Google JavaScript Application programming interface (API). The housing authority (HA) of Hong Kong provided the name list of the public housing and the HA subsidized sale flats. The name lists were also converted to the geographical coordinates using Geocoding. The location information of the private housings which is unavailable from the local government was extracted using the Web scraping from Amap.com. All the building use data were converted to point type in the GIS format based on the extracted coordinates.

Table 2. sources to extract building use types in Hong Kong

Sector	Building use	Source	Local or global	Link
business	Retail	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/rehabsociety-access-accessibile-

				facilities/resource/44bd093c-756b-4c1e-b2f7-a8674503ff89
	Office	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/hk-landsd-openmap-geo-referenced-public-facility-data
	Accommodation	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/hk-had-json1-licensed-hotels-and-guesthouses
	Health	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/hospital-hadata-health-care-facilities
	Education	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/hk-edb-schinfo-school-location-and-information
	Restaurant	Data.gov.hk	Local	https://data.gov.hk/en-data/dataset/rehabsociety-access-accessibile-facilities/resource/44bd093c-756b-4c1e-b2f7-a8674503ff89
Residential	Public housing	Housing authority	Local	https://www.housingauthority.gov.hk/en/global-elements/estate-locator/index.html
	Private housing	Web scaping from Amap.com	global	

	HA subsidized sale flats	Housing authority	Local	https://www.housingauthority.gov.hk/en/global-elements/estate-locator/index.html
Industrial	factories	Housing authority	Local	https://www.housingauthority.gov.hk/en/global-elements/estate-locator/index.html

b). extraction of building morphology

Building morphology was obtained by a simple and efficient approach using open data [45]. The Maps Static application programming interface (API) was used to extract the building footprints and the building heights were generated from a free digital surface model named the ALOS World 3D model with a resolution of 30 m (AW3D30). A spatial join was then applied in GIS between the extracted points of building use and the extracted building to assign the building use attributes.

Thereafter, the building footprints and building heights were used to calculate the BVD for each building use. The BVD is determined by the total building volume divided by the land area:

$$BVD = \frac{\sum_{i=1}^{N}(C_i \times h_i)}{S_L} \quad (1)$$

where i is the building on the land area, C means the area of building, h represents the building height and S_L is the land area size. The land area was determined as 100m.

c). building emissions mapping

The total emissions from buildings (industrial, business and residential sectors) were further refined as the emissions from each building use, based on the percentage of the energy consumption of each building use in each sector. Thereafter, the emissions from each building use were proportionally assigned to each building based on the BVD for each building use. Therefore, the building carbon emissions of a certain pixel p can be calculated as:

$$CE_p = CE_i \times \frac{E_j}{E_i} \times \frac{BVD_p}{\sum BVD_j} \quad (4)$$

where i and j represent the sector and the building use in the sector for the pixel p, respectively. E means energy consumption. BVD_p is the BVD value for the pixel p and the $\sum BVD_j$ is the total BVD value for the building use j.

2.3.3 spatial mapping of carbon emissions in the transport sector

a). traffic flow estimation

The Hong Kong transportation data released by the Hong Kong Transport Department were used to simulate the traffic flow on the road network. In the Annual Traffic Census 2016, the annual average daily traffic (A.A.D.T.) of 1662 counting stations in Hong Kong were surveyed. In this study, we used the Lagrangian model proposed by Xia and Shao [46] to simulate traffic flow on a complex road network based on the A.A.D.T.. This simple method will be quite efficient if there is sufficient road network data.

b). transport emissions mapping

Transportation emissions from fossil fuels mainly consist of road traffic emissions, civil aviation emissions, and marine emissions. The civil aviation emissions and marine emissions were calculated based on the data from the civil aviation department and Hong Kong energy end-use report [37], respectively. Therefore, the emissions from civil aviation and marine were directly assigned to the geographical location of the airport and the ferries. The indirect emissions in the transport sector are the emissions from the MTR. So, the transportation emissions from electricity were equally assigned to the rasterized grid of the MTR route. Emissions from the road network were calculated by excluding the marine, civil aviation and MTR emissions from the total transport emissions. The road network emissions were distributed to the spatial grid of the road network based on the proportion of the traffic flow.

The total urban carbon emissions were mapped out by aggregating the emissions from different sectors. The emissions were finally averaged in each Tertiary Planning Unit (TPU) of Hong Kong for further planning recommendation. TPU was designed for town planning purpose and there are total 291 TPUs in Hong Kong.

3. RESULTS AND VALIDATION

3.1 Total carbon emissions

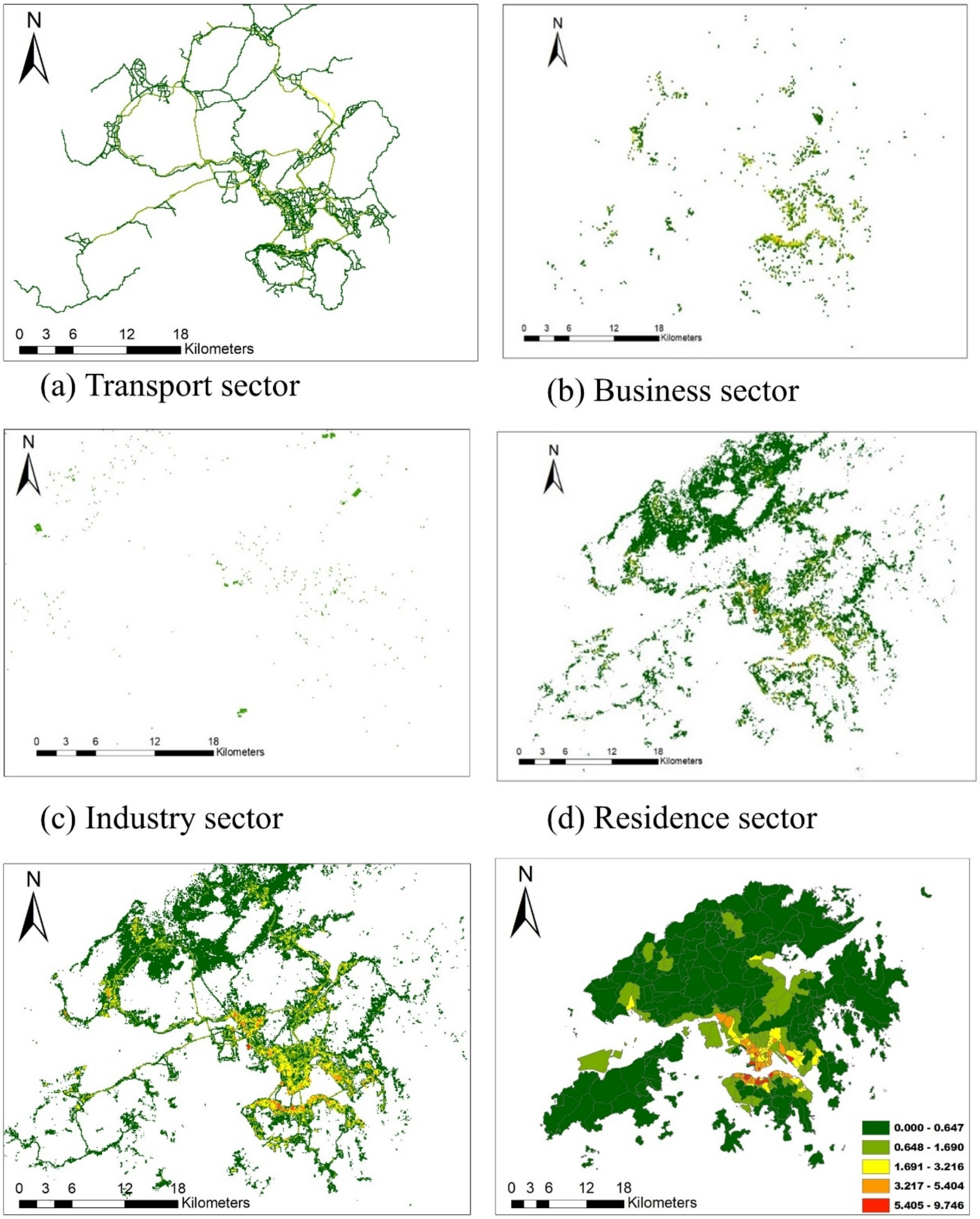
The total emissions were 42.09 Mt in 2016, which is closed to the emissions (41.7 Mt) published by Environmental Protection Department of Hong Kong [35], and the emissions from the global carbon project (43 Mt). 33.55 Mt emissions are from buildings (residential, business and industrial sector), and 8.54 Mt from the transport sector. Buildings are the major contributors to carbon emissions and produce over 80% of the entire emissions. Buildings are also identified to consume more than 90 percent of the electric power. 19% of the emissions come from Oil & coal products, which are mainly consumed in the transport sector. TownGas & LPG contributed to the least carbon emissions among all fossil fuel types.

Table 3. Total carbon emissions by sector (Mt)

Sector	Oil & coal products	TownGas & LPG	Electricity	Total
residential	0.00	1.15	8.50	9.65
business	0.47	0.93	20.47	21.87
industrial	0.39	0.06	1.57	2.03
transport	6.97	0.93	0.63	8.54
Total	7.84	3.08	31.18	**42.09**

3.2 Spatial distribution of urban carbon emissions

The emissions from different sectors as well as the total emissions were mapped out on a 100m-resolution raster grid (Fig. 3). The areas and TPUs of high emissions can be identified. For the transport sector, high emissions were identified in the Cross-Harbour Tunnel and some major roads connecting the New Territories and Kowloon. The emissions from the business sector are the largest among all sectors. Commercial buildings are mainly located in Kowloon and Hong Kong Island, and the high emissions in this sector are concentrated in these areas. Emissions from the residential sector are relatively low but cover a large area of Hong Kong. There are few industries in Hong Kong so that the emissions from the industrial sector are not evident from the mapping results. The total emissions mapping can reflect that the high-density urban areas in the central of Hong Kong have higher emissions and should be taken seriously into account in the low-carbon development. Also, the results are capable of identifying the variations of carbon emissions across different buildings. The emissions of each TPU were summarized in Fig. 3 (f) and TPUs with high emissions such as Yau Tsim Mong, Central & Western can be detected, therefore, the local planners and policymakers can target these TPUs for developing low-carbon strategies.



(a) Transport sector

(b) Business sector

(c) Industry sector

(d) Residence sector

(e) Total emissions

(f) Total emissions by TPU

Fig. 3. carbon emissions in (a) transport sector, (b) business sector, (c) industry sector, (d) residence industrial sector, (e) total emissions and (f) average carbon emissions in each TPU (unit: Kt)

3.2 Cross comparison with the EDGAR data

The modelling results for Hong Kong were validated by comparing with the corresponding results from the EDGAR database [11, 47]. The EDGAR data from the building sector (1A4+1A5) and the transport sector (1A3b, and 1A3c+1A3e) were used. Only the EDGAR cells completely covering Hong Kong were chosen. Ten cells of the EDGAR dataset are available for validation in Hong Kong. The original high-resolution results were aggregated to the same spatial grid and unit of the EDGAR data for comparison (Fig. 4). Fig. 4 (a) and (b) represent the building emissions from our results and the EDGAR, respectively. Fig. 4 (d) and (e) demonstrate the transport emissions in this study and the EDGAR. Fig. 4 (c) and (f) reveal the differences between our results and the EDGAR in building and transport sector.

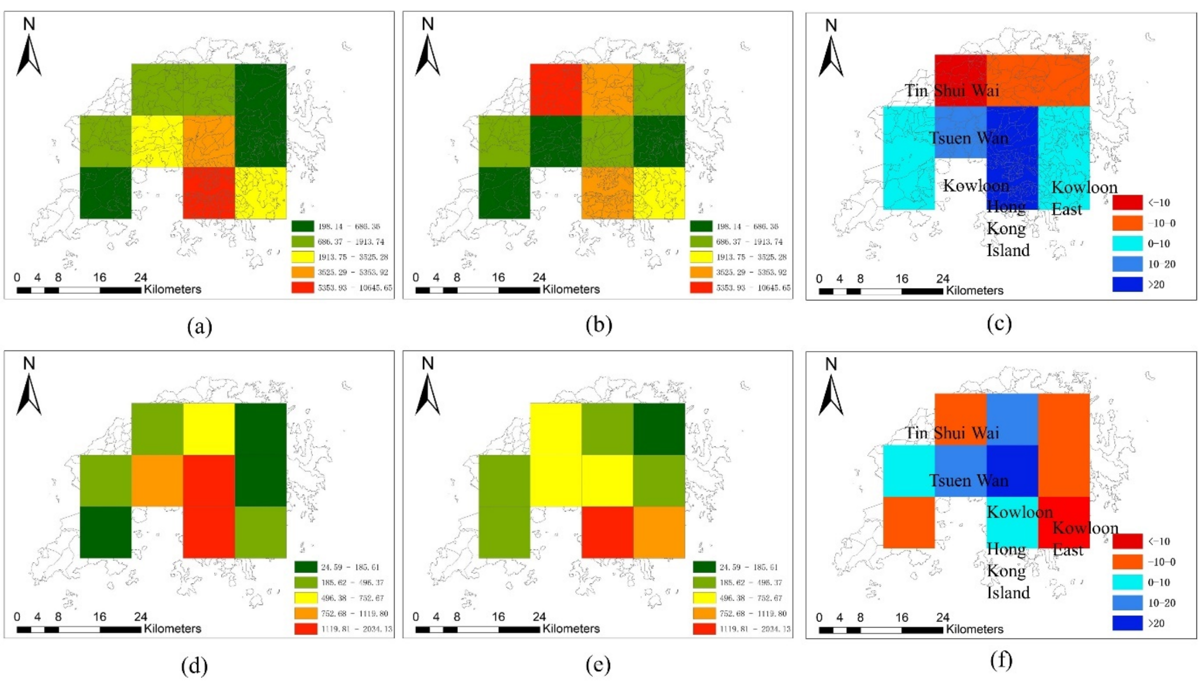


Fig. 4. comparison of the results with EDGAR (a) Buiding emissions from this study; (b) Buiding emissions from EDGAR; (c) difference between (a) and (b); (d) transport emissions from this study (e) transport emissions from EDGAR; and (f) difference between (d) and (e), (unit: Kt).

In general, both results in the building and transport sectors reflect larger emissions in high-density urban areas of Kowloon and Hong Kong Island, and smaller ones in less populated areas. EDGAR reflects larger emissions in Tin Shui Wai in the northwest of Hong Kong where rural land use dominates, while our proposed results demonstrate lower emissions in the same grid for the building sector. The emissions in the building sector should be lower in Tin Shui Wai since there are fewer population and buildings. The high emissions of the EDGAR data can result from the 10km spatial grid which may incorporate the emissions from the adjacent Shenzhen city. The emissions in Tsuen Wan are identified higher in our results than the EDGAR. Tsuen Wan is one of the densely populated old towns and famous for its old industrial areas in which still many commercial activities happen, so the higher emissions from our results can better illustrate the spatial pattern of the emissions of this area.

For the transport sector, our results also detected larger carbon emissions in high-density areas of Tsuen Wan and Kowloon. The two districts are important transportation hubs with tunnels connecting the urban area and the New Territories. There are also a large number of buses to the airport in Tsuen Wan district. Therefore, it is reasonable for our results to have higher values of the transport emissions in these two districts. The EDGAR has a larger emission magnitude in the southeast and northwest of Hong Kong. The Kowloon East in the southeast of Hong Kong used to be an industrial district and is one of the most highly populated districts in Hong Kong. The emissions of the EDGAR were calculated based on population density and industrial process [48]; therefore, this district has a large amount of carbon emissions from the EDGAR database. However, the building density in this district is relatively low in Hong Kong, and the industrial buildings are mainly used as warehouses, or transformed into business or residential buildings since the 1980s

[49]. Thus, the current building use and building density can account for the low carbon emissions in this district from the proposed model.

In sum, our results can better reveal the spatial pattern of the carbon emissions in Hong Kong in both the building and the transport sectors due to the finer spatial grid and the consideration of building attributes. The model shows more reasonable results especially in high-density urban areas with massive commercial buildings.

4. DISCUSSIONS

4.1 Possible application in other cities

Since the spatial emission inventory tool uses open data sources and simple algorithms, it has the potential to be applied in cities worldwide. There are generally four types of input data in the proposed model: statistical energy consumption at the city level, building morphology, building use, traffic flow. The statistical energy consumption data can be provided by the local government and is openly available for most cities in the world. Indeed, some cities don't have such energy use data, and they can be extracted from some global emission databases such as EDGAR. In this model, the building morphology was acquired from AW3D30 and Maps static API. This building morphology extraction method has global coverage and fit-for-purpose accuracy. Moreover, there are also some local 3D building data sources for cities and can serve as the substitute for the building morphology data.

The building use and traffic flow information adopted in this study are local datasets that may not be available in other cities and they could be the major factors influencing the broad applicability of the inventory tool. The building use was extracted and converted by geocoding the name list and web scraping since the Hong Kong government has published detailed building name lists for public buildings. However, the name list of buildings may be inaccessible, and the map service may not contain sufficient building use information for other cities, which may affect the generic application of this approach. The Place API from the Google maps platform can provide point of interest (POI) information such as restaurants, hotels with global coverage and can be used as a usable alternative for building use extraction. Therefore, the methods for building emissions estimation show the possibility to be applied in other cities. Traffic flow was estimated through the traffic census from counting stations which is difficult for researchers to acquire. Meanwhile, there are some traffic flow estimating models using open data, such as the MATSim model, an open-source framework for implementing large-scale agent-based transport simulations [50]. In sum, the inventory tool has the potential of generic application and can be transferable to other cities by using alternative ways to extract building use and traffic flow using open data. The present study demonstrates a generalizable logic pathway of creating carbon emission spatial inventory by the development of the hybrid method and the inventory tool.

4.2 Limitations and possible improvements

The input data adopted in the model can cause uncertainties in estimating carbon emissions (IPCC 2001). These uncertainties can be related the insufficient information about the emission processes, measuring instruments, data quality, etc.[51, 52]. Potential uncertainties of the inventory may come from emission sources and the proxy data.

The emission sources and the proxy data are all derived from open data.3D Buildings retrieved from maps static API and AW3D30 are the emission sources and the proxy data for building emissions in this approach. The accuracy assessment through the linear regression between the extracted buildings and the actual buildings shows that the R^2 for the buildings is around 70% and 72% for the BVD with 100m spatial grid [45]. The R^2 is found to increase with a coarser spatial grid and can reach over 80% with 500m spatial resolution[45]. Therefore, the uncertainty from the 3D building can decrease with the coarser spatial grid. Moreover, there are other open building data sources such as the OpenStreetMap (OSM) or remote sensing data. The OSM building data has a problem in the architectural details and the completeness of the building footprints [53, 54] and can also be uncertain in modelling the urban carbon emissions. The high-quality remote sensing data such as Sentinel-1 SAR data has finer spatial resolution than the AW3D30 and can be used to replace the AW3D30 in the extraction of the building height to reduce the uncertainty from the building.

Moreover, there are many commercial mixed-use residential buildings in Hong Kong. This study regards this kind of mixed-use buildings as residential use due to data availability. Residential building use is the dominant function of such building and mixed-use land use mode is less common in other cities than in high-density cities like Hong Kong. Therefore, the uncertainty of the mixed-use will not affect the generic application of this approach.

Building heating and cooling energy demand can vary greatly in different seasons and years. This study was conducted for the year 2016 to acquire the annual emissions maps. Since the major aim of this pilot study is to demonstrate the workflow, the seasonal and the inter-year variations are not accounted for by the present study. The present study provides an annual result as a demonstration of how the newly developed hybrid method is used. The method itself is readily applicable for other years or periods of interest as long as we feed the inventory tool with statistical energy data of the corresponding period. Future work has been planned to apply the tool for understanding the seasonal and inter-year variations of the carbon emissions.

Finally, since the lack of real emission data for verification is currently still a worldwide issue in most parts of the world, the results can only be validated through cross-comparison with other emission inventories such as GCP, EDGAR. In the future, other real measure instruments will be adopted to achieve a more reliable accuracy assessment.

4.3 Implications for low-carbon city management

In Hong Kong, buildings account for about 90% of the electricity used and over 60% of the carbon emission [55]. The buildings are the major focus of low-carbon development and energy saving for the local government [39]. Since our developed spatial-inventory tool adopts precise building information, it is found that those hotspot areas of urban carbon emissions are located in downtown areas with very high building density. This study results would provide Hong Kong local government with useful information to manage the energy consumption of buildings and make an energy reduction strategy at the district level accordingly, such as developing a district cooling system, adopting renewable energy resources at different districts. This study results could also be used to have a comprehensive understanding of the relationship between the cooling energy requirement and building emissions.

5. CONCLUSION

In this study, a method for creating urban carbon emissions inventory at a high-resolution was developed by incorporating open urban form data. We demonstrated that the approach can be applied in high-density Hong Kong. The emissions from transportation and buildings were generated for entire Hong Kong at both a 100m-resolution grid and the TPU level in 2016. The hotspot areas and TPUs of high emissions were identified. Validation results show that the method has reasonably represented both the total emissions and the spatial pattern of urban carbon emissions of Hong Kong.

The modelling method using open urban form data can more accurately model the spatial pattern of the urban carbon emissions and can be transferable to other cities, therefore contributing to the global collaborative effort in urban carbon emission mitigation. The spatial inventory tool can help support policy decisions regarding urban energy resilience and low-carbon development for different cities. Moreover, it can provide useful information for policymakers of C40 cities that aims to tackle climate change reduce GHG emissions to determine which areas should be targeted to conduct relevant action for improving energy efficiency and carbon emissions mitigation. The map can offer the policymakers with information on buildings and sectors responsible for high emissions, in particular, the variations of the emissions across different buildings. For example, in Hong Kong, with such maps, it would be easier for local government officials to identify those hotspot areas of carbon emission so they could implement energy efficiency ordinance accordingly.

There are also limitations of this study. The uncertainties from the proxy data and emission source can affect the accuracy of the modelling. High-quality building data can be helpful to improve the modelling results. We plan to reduce the above uncertainties by using other high-quality building data in future work. Also, the hourly variation of carbon emissions can reflect the carbon emissions in more detail for better informing the low-carbon development. The hourly variation of the carbon emissions can be modelled in future studies by using popular times of Google Maps API for the building sector, and GPS and machine learning technique for the transport sector.

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