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Using crowdsourced data to estimate the carbon footprints of global cities

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A R T I C L E I N F O

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A B S T R A C T

Cities are at the forefront of the battle against climate change. However, intercity comparisons and responsibility allocations among cities are hindered because cost- and time-effective methods to calculate the carbon footprints of global cities have yet to be developed. Here, we establish a hybrid method integrating top-down input–output analysis and bottom-up crowdsourced data to estimate the carbon footprints of global cities. Using city purchasing power as the main predictor of the carbon footprint, we estimate the carbon footprints of 465 global cities in 2020. Those cities comprise 10% of the global population but account for 18% of the global carbon emissions showing a significant concentration of carbon emissions. The Gini coefficients are applied to show that global carbon inequality is less than income inequality. In addition, the increased carbon emissions that come from high consumption lifestyles offset the carbon reduction by efficiency gains that could result from compact city design and large city scale. Large climate benefits could be obtained by achieving a low-carbon transition in a small number of global cities, emphasizing the need for leadership from globally important urban centres.

1. Introduction

Cities are the core of global climate change mitigation. Their concentration of people, wealth and resources makes cities centres for economic activities, innovation, and culture, and with approximately 55% of the world's population living in cities, they are also the source of 80% of global GDP [1]. The process of continuous urbanization across the globe has the potential to contribute greatly to sustainable development [2,3]. However, urban activities also lead to negative impacts on the environment that often manifest themselves beyond city boundaries. Attributing to cities the carbon emissions associated with the production of goods and services they consume, urban areas covering only 2% of the Earth's land are responsible for approximately 80% of global greenhouse gas emissions [4,5].

Cities therefore bear a tremendous responsibility to play a leading role in the shift to a zero-carbon economy. In the post Paris era, cities have moved from being actors leading the implementation and enforcement of national polices to actors developing and implementing key policies on their own [6,7]. As a consequence, cities are asserting their comparative and competitive advantages to deliver more concrete actions, in many cases more quickly than nations do [8].

To facilitate progress on climate change mitigation in global cities, effective methods to measure the carbon footprints of cities are necessary. Without a globally unified carbon accounting method, the comparison between cities and subsequent responsibility allocation is infeasible [4]. To this end, carbon footprints, also known as consumption-based carbon emissions, are believed to be critical to revealing carbon emissions caused by city activities both within and beyond city boundaries. Weidmann et al. found that the indirect emissions that occurred outside the city boundary in 79 C40 cities accounted for 41% of the total carbon footprint, and if emissions induced by energy production were included, this ratio increased [9].

Some studies have attempted to establish city-level carbon emission inventories and focus on territorial emissions [10,11], however, a widening gap between the territorial emissions and carbon footprints in cities with higher GDP further indicates that developed cities tend to push production-based emissions outside their city boundaries. By estimating carbon footprints, emissions associated with activities occurring in rural areas but serving urban consumers are considered. This reveals information not only about urban lifestyles but also the character of urban infrastructure and the economic structure of a city [12]. Such knowledge serves as the foundation for establishing cooperation to combat climate change between global cities.

Previous studies assessing city carbon footprints usually have massive and costly requirements for data collection and therefore are often limited to a certain country, region, or set of cities. To date, regional city carbon footprints have been calculated via three typical approaches, namely, the environmentally extended input–output (EEIO) analysis, consumer expenditure survey analysis, or an integration of both. If city-

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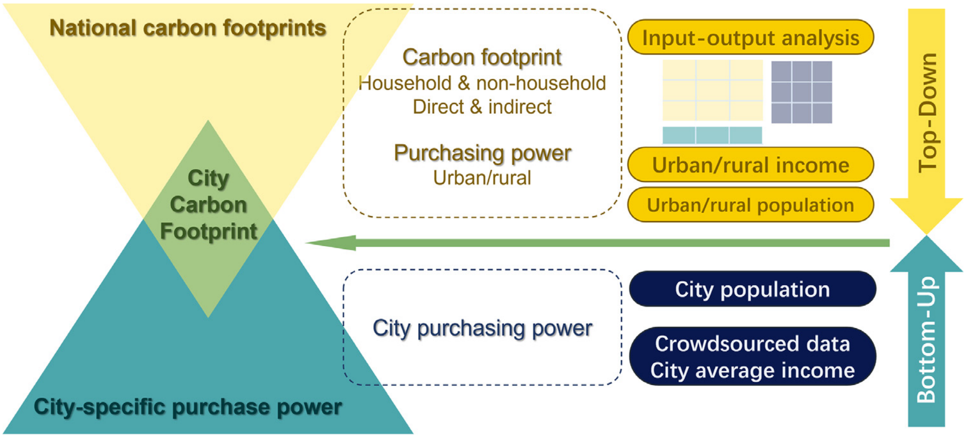

Fig. 1. Framework of the hybrid top-down and bottom-up carbon footprint estimation of global cities.

level EEIO tables are available, an inventory of city carbon footprints can be established [13]. Mi et al. calculated the consumption-based carbon emissions of 13 Chinese cities using the city EEIO tables from regional statistics bureaus [14]. Carbon footprints calculated by consumer expenditure surveys contain more micro consumption details but only account for household footprints and do not include footprints associated with government and capital formation. Lee et al. integrated consumer expenditure survey results and a global supply chain database to calculate the carbon footprints of household consumption in 623 cities in India [15]. Many studies combine both methods to calculate city carbon footprints [16]. Kanemoto et al. integrated the multiregional input–output (MRIO) model and consumer expenditure data to calculate the consumption-based carbon emissions of 1172 Japanese cities [17]. Recently, scholars have used some new approaches, including machine learning [18] or GIS-based data [19] to predict carbon emissions in European cities. These approaches are not only data intensive and time intensive but also constrained to certain regions due to difficult data accessibility [4,20].

A cost- and time-effective method to measure the carbon footprints of global cities has yet to be developed for global assessments. A recently established database, Carbon Monitor Cities, provides near-real-time daily carbon emissions of global cities from 2019 to 2021 [21]. A similar study is the dataset of carbon emissions for global cities by Nangini et al. [22]. These databases are an important step towards timely carbon emission data of global cities. They cover scope 1 and 2 emissions but not scope 3 emissions along the supply chain. For global city carbon footprints, there have been a few attempts to establish a worldwide city carbon footprint database. However, due to the complexity and data intensity of the calculation procedures, these databases are difficult to update, and thus, timeliness cannot be ensured. Moran et al. established a carbon footprint database for global cities by integrating MRIO analysis and global gridded income and gridded population data in 2013 [23]. The study was submitted and published in 2018, showing a 5-year lag of the assessment. Similarly, Marcotullio et al. merged gridded data of greenhouse gas emissions from direct energy use and emissions from power generation to calculate the scope 1 and 2 carbon footprints of European cities in 2000 [24]. Submitted and published in 2013, the assessment has a 13-year lag. In addition, Wiedmann et al. assessed the three-scope greenhouse gas emissions of C40 cities in 2011 by creating city-level EEIO tables using city-specific gross value added data, expenditure surveys, and territorial greenhouse gas emissions data [9]. This study was published in 2020, showing a 9-year lag. The reliance of these methods on intensive data collection thus limits their ability to provide timely results.

In this study, we propose a new hybrid method that integrates top-down EEIO analysis and bottom-up crowdsourced data to assess global city carbon footprints (Fig. 1). Using the crowdsourcing platform, the Numbeo (https://www.numbeo.com/cost-of-living/), to obtain income data at the city level, we estimate the carbon footprints of 465 global cities in 2020 by allocating national consumption-based carbon emissions to cities according to the cities' share of purchasing power. The Numbeo database is a one of the largest cost-of-living databases in the globe and has been used in several studies [25–27]. These results provide policy implications for city development planning and low-carbon consumption transitions. In addition, the method proposed in this study can calculate the most recent carbon footprints of global cities at a low cost. It thus has great potential to calculate the year-by-year carbon footprints of more cities and thus facilitate time-effective studies in this field. In our discussion section, we are able to report that our method produces results that are consistent with current research on city-level carbon footprints and that it provides support for the causal mechanisms elaborated in the literature. Therefore, the reliance and robustness of the method in this study is validated.

2. Methods

This study uses a hybrid approach integrating top-down input-output analysis and bottom-up crowdsourced data to estimate the carbon footprints of global cities. Carbon footprint here is defined as carbon dioxide emissions embedded in the production of goods and services consumed by the residents, governments and capital investment within the city [9]. It covers part of scope 1 emissions (direct emissions excluding those caused by exports), full scope 2 emissions (emissions caused by the consumption of grid-supplied electricity, heating, and/or cooling) and full scope 3 emissions (emissions outside the city boundary which are caused by consumption inside the city). Purchasing power, measured by income level, is adopted as one of the main factors to determine city carbon footprints. Many studies have proved that income explains a large proportion of city carbon footprint variation between different groups [28–30], and the study of Moran et al. [23] confirms the effectiveness of income as a predictor to assess carbon footprints.

Basically, the estimation is conducted in three steps. Firstly, top-down accounting using MRIO tables is employed to calculate national carbon footprints. Secondly, by referring to the specific expenditure patterns and purchasing power of urban and rural residents, national carbon footprints are disaggregated into urban carbon footprints and rural carbon footprints. Thirdly, the urban carbon footprints at national level are further disaggregated into city carbon footprints by the bottom-up crowdsourced data to obtain city-specific income data. Carbon footprints of household, government and capital consumption are all considered. Integrating crowdsourced data and the MRIO analysis, the hybrid framework developed in this study greatly reduces the cost of data collection and hence makes the city carbon footprint data easy to be updated. Here are the details and justification of the method, and discussion on the uncertainties of the method is provided in the Appendix A.

2.1. National carbon footprints

The national carbon footprints are calculated by consumption-based carbon emissions accounting using MRIO analysis. In this study, the EXIOBASE database is employed for the latest MRIO tables and the corresponding satellite accounts for carbon emission data in 2020 [31]. In the EXIOBASE MRIO models, 168 economic sectors and 49 regions (44 countries/regions and 5 regions representing the rest of the world) are included.

Developed by Wassily Leontief in the late 1930s, input-output analysis has been widely used for the environmental impact assessment of economic systems [32]. With the global environmentally extended MRIO tables, direct and indirect carbon emissions embedded in the final consumption of goods and services can be accounted. The basic equation of the multiregional input-output model is depicted in the Eq. (1)-(2):

$$X = (I - A)^{-1} F \tag{1}$$

$$X = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^n \end{bmatrix}, A = \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1n} \\ A^{21} & A^{22} & \cdots & A^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A^{n1} & A^{n2} & \cdots & A^{nn} \end{bmatrix}, \\ F = \begin{bmatrix} F^{11} & F^{12} & \cdots & F^{1m} \\ F^{21} & F^{22} & \cdots & F^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ F^{n1} & F^{n2} & \cdots & F^{nm} \end{bmatrix}, \tag{2}$$

Where $X^s = (x_i^s)$ is the vector of the total output and x_i^s is the total output of sector i in region s; I is the identical matrix and $(I\text{-}A)^{-1}$ is the Leontief inverse matrix. The matrix $A^{rs} = (a_{ij}^{rs})$ is the technical coefficient matrix, and $a_{ij}^{rs} = z_{ij}^{rs}/ x_j^s$, in which z_{ij}^{rs} is the monetary input of sector j in region s from sector i in region r. In the final demand matrix, $F^{rs} = (f_i^{rs})$, f_i^{rs} is the final demand of region s for the products of sector i from region r.

With the carbon emission intensity of each sector, the carbon footprint can be calculated via Eq.3:

$$C = E (I - A)^{-1} F \tag{3}$$

Where C is the matrix of total carbon emissions embedded in goods and services used for final consumption; E is a vector of carbon emission intensity of all sectors in all regions, which is measured by carbon emissions per unit of economic output. Here, the carbon emissions data in 2020 in the EXIOBASE database is based on prediction values and does not include the impact of COVID pandemic. To address the errors introduced by this, we adopted carbon emission data from Global Carbon Budget [33] to proportionally update the emission data. Emissions induced by fossil fuel combustion and cement production are included in this study.

National carbon footprints obtained via MRIO models includes direct and indirect carbon emissions from household and non-household consumption. By summing the corresponding column vector in the carbon emissions matrix C, the carbon footprint induced by household consumption CF_{hh} and non-household consumption CF_{nh} of each region can be obtained. The CF_{hh} and CF_{nh} are the indirect carbon emissions embedded in the goods and services in the household and non-household final consumption. CF_{nh} includes carbon footprints of final consumption expenditure by non-profit organisations serving households, government, inventories, and valuables. From the MRIO database, the direct carbon emissions from final consumption in each country CF_{hh_d} and CF_{nh_d}, mainly from fuel combustion, can also be easily accessed. The direct and indirect carbon footprints of national final consumption will be further disaggregated in the following steps.

2.2. Estimating city carbon footprint according to purchasing power of city residents

Direct and indirect carbon footprints of household consumption at national level are initially disaggregated into rural and urban footprints according to expenditure patterns and purchasing power, and then national urban footprints are disaggregated into city footprints. Non-household footprints are allocated to city residents equally per person. Total carbon footprints at the national level are disaggregated into urban and rural household carbon footprint to eliminate the impact of different consumption patterns and purchasing power on carbon footprints between urban and rural households. This step was conducted at the national level because of the inaccessibility of city-level consumption data between rural and urban residents.

Disaggregation of indirect household footprints, CF_{hh} into urban and rural carbon footprints is accomplished by incorporating the urban/rural household expenditure survey, income, and population data. The CF_{hh} depicts household indirect footprints in 168 sectors and is therefore aggregated into 12 sectors to match the household expenditure patterns. The direct household footprints, CF_{hh_d}, are disaggregated according to rural/urban consumption in energy, water utility and transport, as well as purchasing power.

With the non-household footprints and urban household footprints at the national-level, city carbon footprints are estimated as follows:

$$CityCF_{hh} = (UCF_{hh} + UCF_{hh\_d}) \times \frac{Inc_{city} \times Pop_{city}}{Inc_U \times Pop_U} \tag{4}$$

$$CityCF_{nh} = (CF_{nh} + CF_{nh\_d}) \times \frac{Pop_{city}}{Pop_U + Pop_R} \tag{5}$$

$$CityCF = CityCF_{hh} + CityCF_{nh} \tag{6}$$

Where $CityCF_{hh}$ is the total direct and indirect carbon footprints by city household consumption; $CityCF_{nh}$ is the total direct and indirect carbon footprints by city non-household consumption; $CityCF$ is the total carbon footprints in a city; UCF_{hh} and UCF_{hh_d} are indirect and direct household consumption footprints of urban residents in a country; CF_{nh} and CF_{nh_d} are indirect and direct non-household consumption footprints; Inc_{city} and Pop_{city} are average income and population of a city; Inc_U is the average income and Pop_U is the population of urban residents in a country; Pop_U and Pop_R are the population of urban and rural residents in a country. With city carbon footprints, the income Gini and carbon Gini coefficients are calculated. Details of the calculation can be seen in the literature [34].

2.3. Data sources

The MRIO model used in this study is accessed by the EXIOBASE [31]. The carbon emission data are therefore obtained from the satellite accounts in the EXIOBASE database. National rural and urban income and population data are collected from Euromonitor Passport database (https://www.portal.euromonitor.com/portal/magazine/homemain/). Income data are displayed as total disposable income at national level rather than per capita, indicating that this variable does not need to be multiplied by population anymore. The rural and urban income data of Cyprus, Luxemburg, and Malta are not provided by Euromonitor and thus collected from Eurostat database (https://ec.europa.eu/eurostat). As disposable income data includes fewer countries than those included in the population dataset, the average income per capita in the ROW areas are calculated first and then multiplied by the population in the area. Population and income data at the national level are all collected in the base year 2020.

Urban and rural household expenditure patterns of all the 44 countries/regions in the MRIO model are collected (Table A1 in Appendix A). The household consumption survey of all the 44 countries in the EXIOBASE input-output model was applied in this study to disaggregated national household carbon footprints into urban and rural household footprints. For the sector classification method, most countries follow the Classification of Individual Consumption According to Purpose (COICOP) of the United Nations to classify consumer expenditures, while expenditure pattern in the World Bank database is classified into 12 sectors in a different way. The consumption patterns of five ROW areas are proxied by similar countries in the areas following labor accounting in the EXIOBASE [31].

City income data are collected from an crowdsourcing platform, the Numbeo [35], which enables people worldwide to record the income and expenditure in their city. Data on this website are public and can be downloaded directly. From this platform, we collected the average monthly salary after tax in each city in 2020. The available data in 2020 contains income data for 465 cities from 116 countries/regions and carbon footprint of these cities are estimated in this study.

City population data are obtained from the UNData database (https://data.un.org/Data.aspx?d=POP&f=tableCode%3a1) and the database of City Population (https://www.citypopulation.de/). The UNData provides city population for some cities in this study. The population data for the missing cities in the UNData are collected from the City Population database, where most of the population data are from the national statistical bureaus. To ensure the two databases match with each other, we compare the data from both and calculate the difference between them. City proper population in the same year as from the UNData was estimated using population and annual change rate data in the City Population database, and the differences between the two databases were compared. Finally, the average discrepancies are 8%, indicating the two databases can be substituted with each other. It is noticeable that the definition of a city, depicting the boundaries of a city, in the two databases is comparable. In the UNData, population in city proper and/or urban agglomeration of a city is provided, while in the City Population database, population in city proper, urban agglomeration and metropolitan of a city can be obtained. In this study, we mainly refer to population in city proper to define the boundary of a city (except Indian cities as the population of urban agglomeration is officially reported).

3. Results and discussion

3.1. Carbon footprints are concentrated and unequally distributed in global cities

The carbon footprints of these cities are disproportionately large and related to their populations. The total carbon footprint of the 465 cities in this study was approximately 6.23 billion tons CO_2 in 2020 (Fig. 2), and the total population of these cities was approximately 0.77 billion. This indicates that the 9.9% of the global population that lives in these cities causes 17.9% of global total carbon emissions [33]. The average carbon footprint per capita of these cities is approximately 8.11 t and is therefore nearly twice the global level (4.48 t), with more than half of the carbon footprint caused by household consumption (Fig. 3C, 3D).

Carbon abatement of a small number of cities could result in large climate benefits globally. Calculating the average carbon footprints per capita and the standard deviation (SD, denoted as σ) of all the cities, three levels of super emitters were identified, and the global emission reduction is calculated in three decarbonization scenarios. The scenario settings are designed with reference to previous studies [36]. The cities having carbon footprints larger than the average carbon footprint of all the cities are referred to as above-average emitters. One SD super emitters refer to cities having carbon footprint 1σ larger than the average level, and two SD super emitters refer to cities having carbon footprint 2σ larger than the average level. In the three abatement scenarios, we assume that 2 SD cities, 1 SD cities and above-average cities reduce the carbon footprint per capita to the average level of all the 465 cities, respectively. The total carbon emission reduction benefits at the global level were calculated in the three scenarios. If the above-average cities applied carbon abatement measures and cut the carbon footprints, 1.6 billion of carbon emissions could be avoided globally, accounting for a quarter of the total carbon footprints of all the cities. Low carbon transition in 1 SD leads to 1.1 billion carbon reduction benefits globally (with only 9% of the total population contributing to 18% of the total carbon footprint reduced). If the 2 SD cities could reduce their carbon footprint per capita, this cuts 0.7 billion carbon emissions globally, accounting for 11% of the carbon footprints in all the 465 cities (with only 4% of the total population). This indicates that carbon reduction in the top emitters brings disproportional climate effects.

This concentration of carbon emissions suggests an urgent need and opportunity for leading global cities to take action to mitigate climate change. This can include low-carbon infrastructure investment, supply chain management, and nudging consumer behavior transition towards cleaner consumption, and government regulations as well as price mechanism are important in low-carbon transition [37,38]. A positive relationship between the estimated carbon footprint and city GDP demonstrates the reliability of the method (Fig. A1 in Appendix A). In addition, comparing these results with published work, the average difference between our results and those of Moran et al. is approximately 24.7% [23]. Given the uncertainties inherent to footprint analysis, these results are well within what would be expected [39]. A comparison between carbon footprint in this study and the scope-1 emissions calculated by Global Carbon Budget shows that the estimated carbon footprints per capita of ten selected cities are 252% larger than the scope-1 emissions of those cities averagely, which is much larger than the differences between this study and the literature (24.7%). The results confirm the necessity of measuring city carbon footprint to better reflect the responsibility of global cities, especially the megacities in addressing climate change.

In addition to an unequal distribution of emissions between cities in this analysis and wider urban areas, an unequal distribution of emissions is found within the cities assessed. Specifically, the top 10% of people by income are responsible for 25% of the total carbon footprint in these cities, and the top 20% of earners are responsible for 41% of the total emissions, while the bottom half of people account for only 23% of the total footprint. This degree of emissions inequality revealed in this study is much lower than the inequality between global nations. Bruckner et al., for example, found that the top 10% of emitters contribute almost half of global carbon emissions, while the bottom half of emitters contribute only one-tenth [40]. The lower inequality in this study is likely attributed to the sample of cities we assess. Due to data being primarily available for larger cities and capital cities, incomes would be expected to be significantly higher than average. A Zif's law test shows that there is a lack of small cities in this study (Table A2 and Fig. A2). The inequality in this study is therefore not representative of the global situation, and disparities between rural and urban areas and between developed and less-developed cities lead to higher inequality at the global level.

Comparing the income Gini coefficient and the carbon Gini coefficient for these cities reveals differences between cities in wealthy and developing nations (Fig. 4). The income Gini coefficient and carbon Gini coefficient are relatively low in cities from developed countries (0.23 and 0.25, respectively) and slightly higher in cities from developing countries (0.35 and 0.43, respectively). This suggests that these cities may represent enclaves of higher incomes within their respective nations. Less-developed countries experience worse conditions regarding carbon inequality. In addition, the income and carbon Gini coefficients at the global level are even higher (0.50 and 0.43, respectively), especially for the income Gini coefficient. This indicates that the observed inequality in the carbon footprints in these cities mainly results from the development gap between the developing countries and developed countries and within the group of developing countries. This implies an opportunity, and a risk, of the consumption patterns of the highest income cities being emulated by rapidly developing cities, with consequences for our ability to meet our climate targets. It is noticeable that

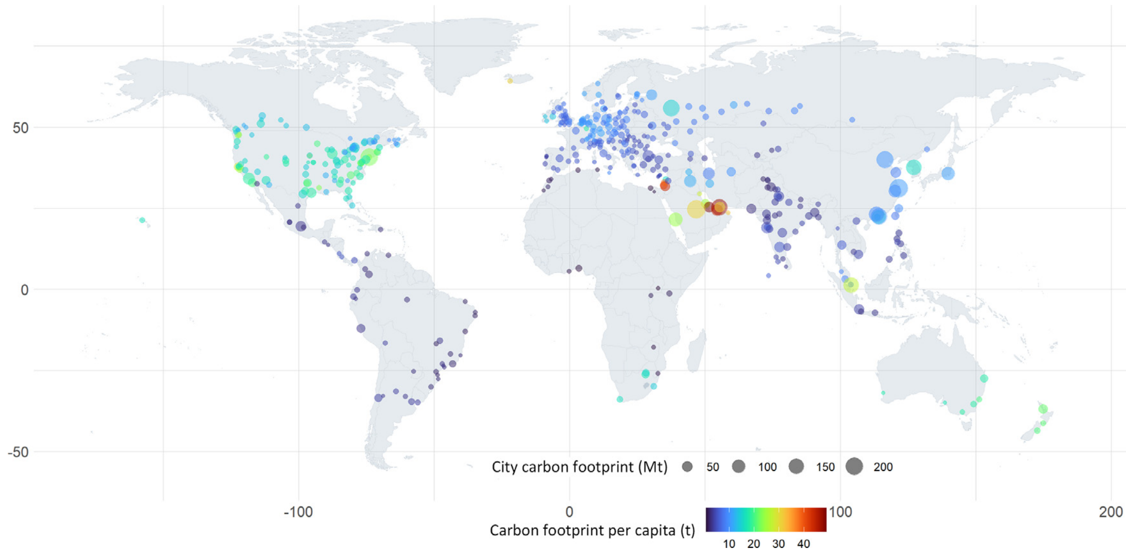

Fig. 2. Total carbon footprint and per capita footprint of global cities.

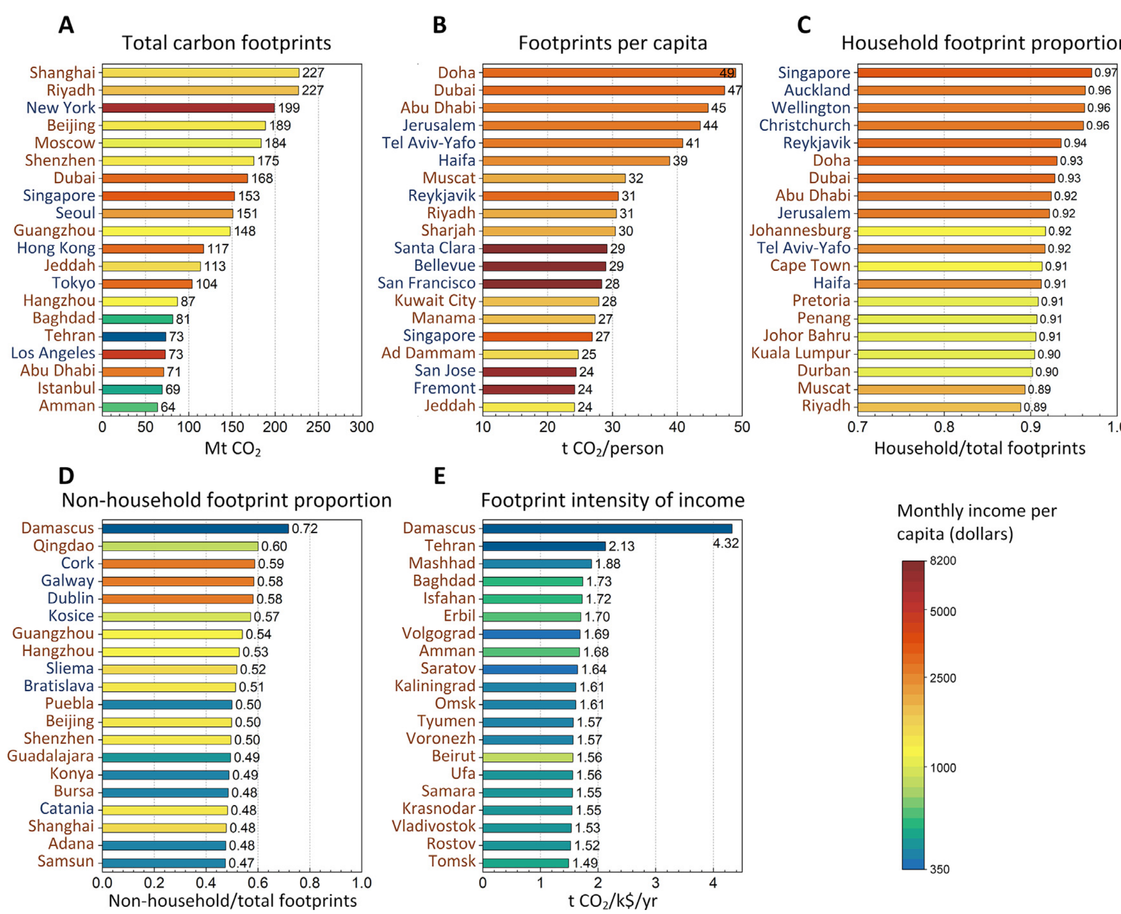

Fig. 3. Top 20 cities globally by carbon footprint and carbon footprint per capita. Cities with names in blue are from developed counties/regions and cities with names in orange are from developing ountries/regions.

the carbon footprint Gini coefficient is less than the income Gini coefficient across cities.

Inequality in the distribution of carbon footprints could lead the emerging and poor group to be more vulnerable to the economic burdens of carbon reduction and climate adaptation. The carbon footprints of the top 20 cities in developing countries are only approximately half of the footprints in developed countries, and the share of emissions from households is higher. However, the footprint intensity of income and the volume of carbon per unit are much lower in developing cities (Fig 3E, A3, A4). The global top 20 cities by footprint intensity of income are all from developing countries, ranging from 1.49–4.32 t CO_2 per thousand dollars. In contrast, the income footprint intensity of the top 20 cities in developed countries ranges from 0.53–1.34 t CO_2 per thousand dollars. This suggests that emissions reductions would be more likely to impact

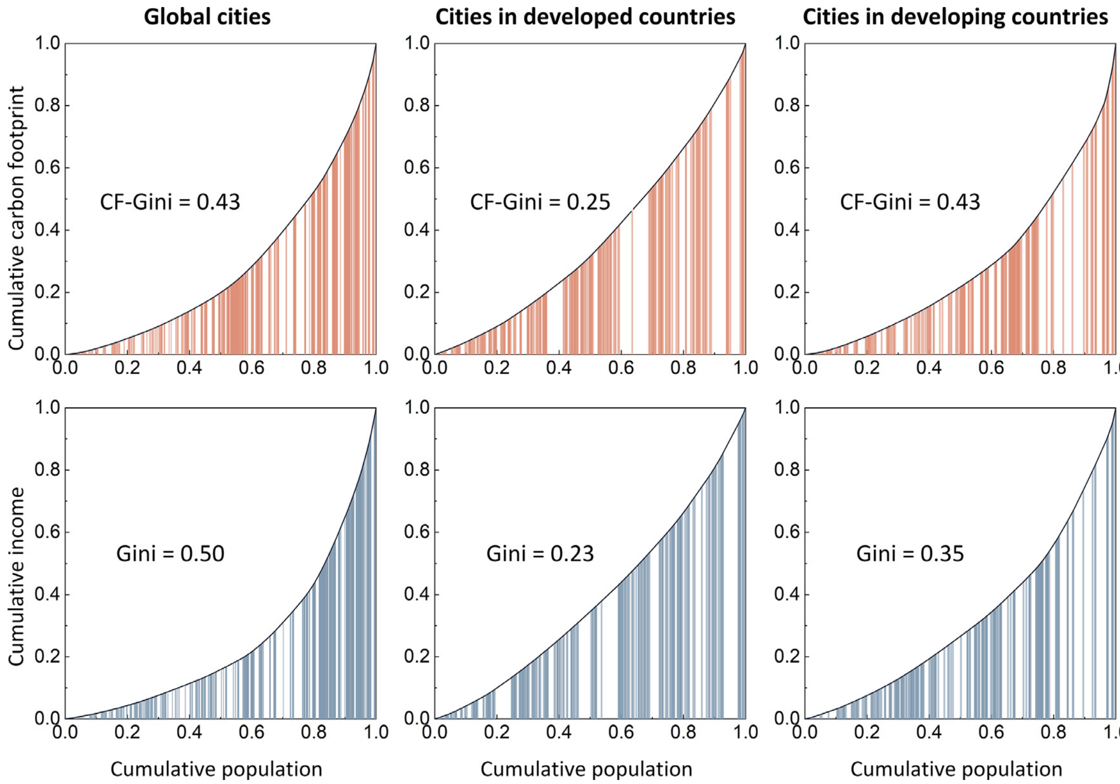

Fig. 4. Gini coefficients and carbon Gini coefficients of cities across the globe, in developed countries and in developing countries.

basic necessities, such as food and shelter, in developing country cities [41].

3.2. Income, scale, and density are determinants of carbon footprints

Affluence, population, and the regional carbon intensity of consumption together determine the carbon footprint of a city (Fig. 3A, 3B). Among the top 20 cities by income, six cities are in Switzerland, and 14 cities are in the US (Table A3, Fig A3). Among the top 20 cities by carbon footprint per capita, however, most are cities in the US and Middle East, illustrating the important role of regional carbon intensity. The carbon footprints of cities in Switzerland and the US are approximately 10.2 t and 18.6 t per capita, respectively, which is in accordance with the literature [42,43]. The high carbon footprints in the US cities are mainly driven by income effects, indicating higher income in these cities leads to higher consumption and therefore higher carbon footprints. The disparities of carbon footprints in Switzerland and Middle east cities are mainly driven by regional carbon intensity.

Population plays a key role. The top 10 cities by population in this analysis are all in developing countries (Table A3, Fig A4), and seven of the top 10 cities by carbon footprint are in developing countries. For example, three Chinese cities, Shanghai, Beijing, and Shenzhen, are among the top 10 cities by total carbon footprint and their population ranks in the top 3 across all the cities in this study, even as the carbon footprints per capita of Chinese cities are not high in relative terms. Consumption aggregation is a main driver and a recent study shows that population agglomeration increases city carbon emissions by industrial structure and transportation effects [44]. However, the affluence effect and regional carbon intensity of consumption can mitigate the role of population. New York, which has only 40% of the population of the most populous city, Shanghai, ranks third by carbon footprint. The average monthly income in New York is $6023 per capita, while it is less than a quarter as high at $1459 in Shanghai. The average carbon footprint of Chinese cities in this study is 9.8 t per capita, which is only half of

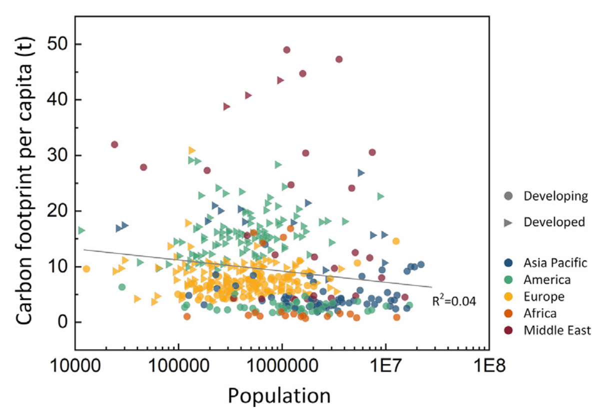

Fig. 5. City carbon footprint and population. Developed and developing refer to cities in developed or developing countries.

the average in US cities. The carbon emissions associated with expenditures from high income and carbon-intensive lifestyles should therefore be seriously considered as an impediment to low and noncarbon urban areas, for example, excessive energy consumption for heating and cooling [45]. The population of the city proper is used in this study, and we provide an uncertainty analysis regarding the city definition, i.e., city proper, urban agglomeration and metropolitan area, to call for a clear definition of a city when analysing city carbon footprints (Fig. A5).

No meaningful relationship is found between carbon footprints per capita and city population (Fig. 5.). This may be explained by different factors working in competing directions. A scale effect, i.e., economies in scale in the provision of goods and services, may result in higher energy efficiency and therefore a lower carbon footprint per capita in a larger city [46]. However, larger cities may concentrate higher income populations, leading to higher emissions. Regional lifestyle factors also play a role in explaining the relationship between carbon footprints and

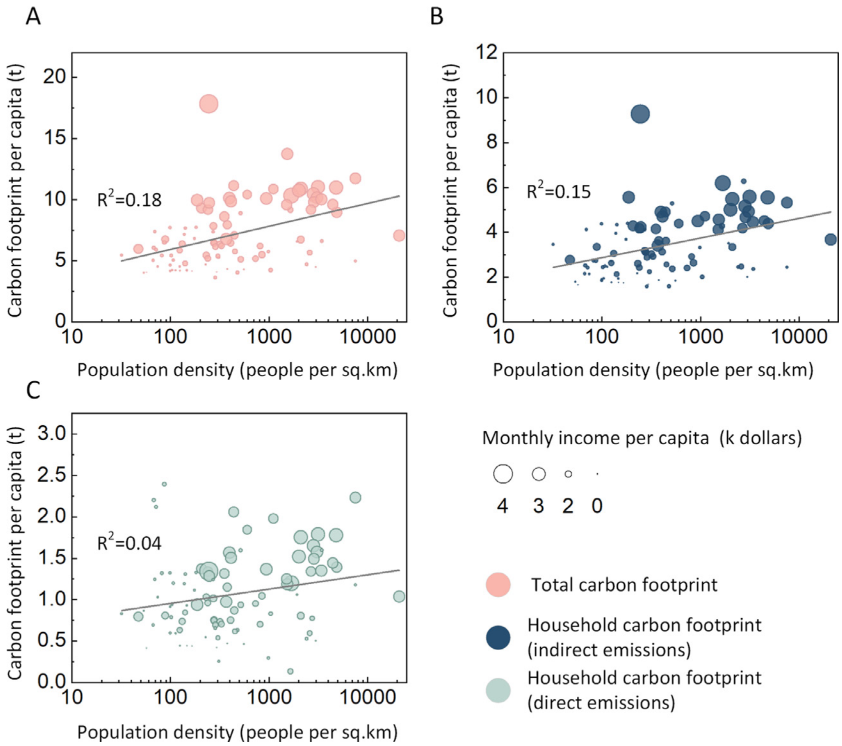

Fig. 6. Carbon footprint per capita and income are higher in dense cities.

population. Cheng et al. found that larger cities usually have lower carbon emissions per capita because larger cities employ more advanced power generation technologies and have higher energy efficiency [47]. In contrast, Kanomoto et al. found that with the expansion of the city population, the footprint per capita of most cities initially increases but starts to decline when the population is larger than 400 thousand [17]. Smaller cities have smaller footprints per capita in part because people in small cities have lower incomes and therefore lower consumption. A regression analysis is further conducted to explore whether the correlation differs in different regions and whether the scale effect exists after controlling for income (Tables A4 and A5). A weak relationship between population and per capita footprint can be observed while such scale effect could only explain less than 0.1 of the variances in per capita footprint (R^2<0.1), indicating other explanatory variables should be included. When income is taken as a controlled variable, the scale effect is not significant anymore, suggesting that scale effect is overwhelmed by income effect. Globally, per unit change in income leads to 0.69-unit changes in per capita carbon footprint. Income effect can explain 46% of the variance in per capita footprint and the remaining variance may be caused by factors such as regional production technology and lifestyle, etc. We should be aware that the income effect found here may owing to the method using income data to estimate city carbon footprint in this study, but the scale effect is not significant considering it fails to explain any variances in carbon footprint even income is not controlled.

On the other hand, we find a weak positive relationship between population density and carbon footprints per capita in European cities. Given the wider literature on this subject, this relationship may capture socioeconomic indicators rather than geographic indicators [48]. Theoretically, a city with higher population density can increase resource efficiency and thus reduce direct emissions per capita [28,29], which is known as a density effect. A compact city form creates low-carbon benefits through smaller housing area and shorter transport distances and through the opportunity for transport to be shifted to public transportation [29,49–52]. Evidence from the literature supports the density effect. For instance, Goldstein et al. showed in their research that the carbon footprint per capita of household energy consumption is lower in densely populated areas in Boston and Los Angles [30]. There are also some studies which disagree with the density effect. with different. Lee et al. found that per capita footprints are positively correlated with population density in cities with a lower poverty ratio [15]. Gill et al. found that dense cities show lower direct footprints but higher indirect footprints and the increased indirect footprints mainly result from the increased expenditures and smaller family sizes in dense cities [29]. Similarly, Ahmad et al. argued that the higher emissions in dense areas are a result of higher income because the density effect is not observed when income variation is controlled, indicating that the income effect can counteract the density effect [46]. In this study, we find that both direct and indirect carbon footprints rise in dense cities (Fig. 6 and Table A6). Specifically, indirect footprint in dense cities rise and therefore leads to significant increase in total footprint per capita, although only 15% of the variances in indirect footprint can be explained. This can be explained by increased affluence and smaller family size in dense cities as in the literature [29]. We further take income as a controlled variable and the results show that the density effect is not significant after controlling for income, illustrating that the higher footprints in dense cities may have resulted from higher income. Income effect explains 71% of the variances in per capita carbon footprint in European cities. The explained variance is higher than that of the previous model (46% in the preceding paragraph) because only European cities are adopted here (due to data availability). Accordingly, the variances in other impact factor like regional lifestyle and production carbon intensity are less.

Carbon footprints show regional similarities, which means that cities in a region tend to have similar carbon footprints. This reflects the impact of cultural and political factors in driving emissions footprints. Several cities in the Middle East show the highest carbon footprint per capita. This is related to the reliance of these regions on fossil fuel energy consumption. People in North American cities (cities in developed American countries) usually have very high carbon footprints, while people in European cities have lower footprints (Fig. 6). Income is a key driver of emissions across all places; therefore, comparing places with similar levels of income can offer insights. North American cities, for example, have the highest per capita footprint, while European cities have a significantly lower footprint per capita. Factors such as the rate of car ownership, energy prices, density, and the economic makeup of a city are among the drivers of these differences [9]. Intraregional cooperation can boost connections between cities to help them address similar challenges. Techno-economic, political, and cultural challenges can therefore, to a certain degree, be proxied by geographic proximity, emphasizing the need for intraregional cooperation and learning and top-down national government approaches to climate action that cut across urban areas.

Relationships between cities that derive from income, population, density and other factors provide insight into the ways interregional urban cooperation may be best developed. New York, London and Paris, by this approach, may have more to learn from each other than New York, Houston and Cincinnati. Across regions, cities can build networks to learn from each other. In this context, networks focused on secondary and tertiary cities may be important. Global megacities, such as C40 cities, more frequently have the capacity to develop climate approaches and are better served by existing networks.

3.3. Uncertainty analysis

There are uncertainties are induced by several assumptions in this study. First, in term of city definition (detailed discussion in Supplementary materials), the crowdsourced data represent the city-specific average income level in a broad sense, which means it is hard to ensure that all the contributors are from city proper rather than suburb areas. There are some criticisms about the accuracy of the data on this platform because of anonymous contribution. This would introduce uncertainties, but it is a good starting point to for the present study and with the development of the platform and increasing contributors, the problems will be eased in the future. Second, we assume that the carbon intensity of household consumption is equal within each region. Third, the household expenditure pattern is assumed to be homogeneous within each region. Forth, the non-household carbon footprints are allocated to every person equally. To assess the uncertainties, we compare the average differences between the carbon footprints in this study and the literature. To minimize the impact of the time lag between the results in this study and the literature, we updated the city carbon footprints in Moran et al. [23] by using the growth rates of national consumption-based carbon emissions from 2013 to 2020 in the Global carbon budget [33]. The disparities between the results of this study and those of Moran et al. approximately 24.7% [23], which are acceptable considering the uncertainties inherent to footprint analysis [39]. In addition, such disparities are in consistence with the results in the literature, where 10%-20% higher real estate prices are found of the Numbeo data and official data in several European cities [53].

4. Conclusion

A novel hybrid method integrating top-down input–output analysis and bottom-up crowdsourced data is established in this study to estimate carbon footprints of global cities. The method enables us to conduct an unprecedented and the latest assessment of global city carbon footprints in 2020, reducing the time lag of such assessment greatly from 5–13 years to 1–2 years. In addition, the difference between the city carbon footprints in this study and in other studies shows that the estimation results are valid and reliable. The causal mechanisms elaborated in the literature are supported by the results in this study, indicating the robustness of this assessment. The time- and cost-effectiveness of the method ensure the timeliness of city-level carbon footprint analysis and function as a basis for city comparison and responsibility allocation.

The concentration and unequal distribution of carbon footprints in global cities are revealed in this study. Using crowdsourced data, we estimate the carbon footprint of 465 global cities, including direct and indirect emissions from household, government, and capita consumption. Carbon emissions are highly concentrated in these cities and within these cities, unequally distributed carbon footprints are observed. Such inequality is mainly the result of unbalanced economic development between less-developed, developing and developed countries. The highly concentrated carbon emissions caused by consumption in the cities indicate the necessity of consumption-side decarbonization for climate change mitigation.

The results also show the disproportional climate benefits gained from the low carbon transition of a small number of cities, and therefore the need for affluent cities to take more responsibility for carbon reduction. Socioeconomic indicators affect the city carbon footprint more than geographic indicators. Specifically, income overwhelms any influence from population or density. This indicates a global challenge of addressing high-carbon lifestyles for neutrality targets to be met. Regarding sustainable city development, the transformation of the economic structure, energy mix, supply chain sources and consumer behavior are important in city-level climate change mitigation. Inter- and intraregional cooperation offers an underrealized opportunity for knowledge sharing. For example, cities with similar affluence and in Europe and North America have a common need to focus on supply chains that support urban consumption and to find ways to finance the unlocking of urban energy and transport systems. Middle Eastern cities should try to promote the energy transition and develop greener and cleaner energy. The concentration of emissions from these cities, both direct and indirect, emphasizes the need for their leadership.

There is enormous potential for the method used in this paper to reveal the carbon footprints of more cities and to establish a panel database. Crowdsourced data can greatly reduce the difficulty of data collection and are more cost-effective than other methods in the literature. Moreover, the crowdsourcing platform can provide time-effective income data, and therefore, the carbon footprint of cities can be easily updated with other indicators available. The utilization of crowdsourced data in this study helps us offer timely estimation of the carbon footprint of global cities, and the results are consistent with the literature. The disparities between this study and others in the literature are acceptable considering the difficulty of such estimation. These results validate the data and method used in this study. With the influence and popularity of the platform, more cities will be included, and their carbon footprints can be easily estimated. Additionally, the year-by-year income data provided on the platform make a panel database feasible. These data will promote time-series analysis of the city carbon footprint and offer insightful policy implications for city development.

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Declaration of Competing Interest

The authors declare no competing interests.

CRediT authorship contribution statement

Xinlu Sun: Data curation, Methodology, Formal analysis, Writing – original draft. **Zhifu Mi:** Supervision, Conceptualization, Writing – original draft. **Andrew Sudmant:** Conceptualization, Methodology, Writing – review & editing. **D'Maris Coffman:** Writing – review & editing. **Richard Wood:** Data curation, Writing – review & editing.

Data Availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adapen.2022.100111.

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