Consumption-based screening of climate change footprints for cities worldwide

Ohms, Pernille K.; Laurent, Alexis; Hauschild, Michael Z.; Ryberg, Morten W.

Published in:
Journal of Cleaner Production

Link to article, DOI:
10.1016/j.jclepro.2022.134197

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Journal of Cleaner Production 377 (2022) 134197

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Consumption-based screening of climate change footprints for cities worldwide

Pernille K. Ohms *, Alexis Laurent, Michael Z. Hauschild, Morten W. Ryberg

Section for Quantitative Sustainability Assessment, Department of Environmental and Resource Engineering, Technical University of Denmark, Kgs. Lyngby, Denmark

A R T I C L E I N F O

Handling Editor: Cecilia Maria Villas Bôas de Almeida

Keywords:
Climate change footprint
Consumption-scope
Sustainable cities
Sustainability screening
Multiple regression models

A B S T R A C T

With long-term prospects indicating worldwide increasing urbanization over the next decades, cities are responsible for a growing share of global greenhouse gas emissions. This makes local policies more important in mitigating climate change, and calls for efficient tools allowing local decision makers to measure the impact of urban areas under their control. This study introduces a parsimonious screening tool to cater to this need and allow local governments to gauge and monitor consumption-based climate change footprint of cities. The tool consists of multiple-regression models that operate on easily accessible city data. To demonstrate its applicability, the per capita climate change footprint is estimated for 949 cities. Australian cities are found to have the highest per-capita footprint, averaging 20.4 t CO_2-eq, while South American cities have the lowest per-capita footprint, averaging 8.1 t CO_2-eq. The results are evaluated against IPCC climate change mitigation pathways to judge which cities are on track to an absolute sustainable level of greenhouse gas emissions. Few cities are found to be on track to comply with the necessary levels for 2030, and the findings thus substantiate that cities all over the planet need major actions to comply with the required climate change mitigation.

1. Introduction

Long-term projections predict that urbanization will continue in all regions of the world over the next decades, with the share of the population living in cities globally growing from 56.2% to 60.4% by 2030 (UN-Habitat, 2020). Cities are responsible for an increasingly larger share of global greenhouse gas (GHG) emissions (C40 Cities, 2020), highlighting the importance of climate mitigation and adaptation in cities. The United Nations have dedicated one of their 17 goals for sustainable development (SDGs) to achieving sustainable cities and communities (SDG 11) and city leaders worldwide have started to pass legislation and enact development plans compatible with the Paris Agreement (C40 Cities, 2016; 2020; Watts, 2017; Wiedmann et al., 2021). The C40 Network thus estimates that cities worldwide can deliver about 40% of the reductions necessary to achieve the Paris Agreement (C40 Cities, 2016). City governments are hence key to successfully mitigate climate change, and this increases the importance of local assessments as well as local policies and regulations (C40 Cities, 2020; Revi et al., 2014). Finally, it is essential that the impact of cities on climate change is quantitatively evaluated to allow benchmarking against evidence-based targets to effectively implement transformational climate change mitigation and adaptation in cities (C40 Cities, 2020).

To evaluate the climate change impact from cities, a widely accepted methodology is the Greenhouse Gas Protocol for cities (Arioli et al., 2020) intended for local governments. However, it carries important limitations. The methodology requires extensive calculations, possibly attainable for larger city administrations in developed regions, but not feasible for smaller local governments in developing regions, with typically limited resources devoted to GHG accountings (Erickson and Morgenstern, 2016). Furthermore, assessing and reporting emissions embodied in food, and other products and commodities consumed in the city is not mandatory, and the Protocol does not provide any guidance on how to estimate these. Wiedmann et al. (2021) highlight the importance of considering emissions embodied in these imports and find that, for 80% of the 97 cities collaborating to mitigate climate change within the C40 network, GHG emissions embodied in commodities exceed direct GHG emissions taking place within the city boundaries.

This omission entails a risk of burden shifting and it is hence important that climate change impact assessments consider direct emissions as well as those embodied in the products and services used by the city, i.e. applying a consumption-based perspective. Different

* Corresponding author.
E-mail address: pkroh@dtu.dk (P.K. Ohms).

https://doi.org/10.1016/j.jclepro.2022.134197
Received 4 May 2022; Received in revised form 13 September 2022; Accepted 15 September 2022
Available online 1 October 2022

approaches to do so have been developed over the years, e.g. material flow analysis (MFA) (Alfonso Piña and Pardo Martínez, 2014; C. A. Kennedy et al., 2015; Rosado et al., 2014) and life cycle assessment (LCA) (Dias et al., 2014; García-Guaita et al., 2018; González-García and Dias, 2019; Lavers Westin et al., 2019). With MFA, a top-down approach is applied and an inventory of flows in and out of the city is developed. Although giving useful information at full city scale and including up- and downstream flows, MFA does not interpret these flows in terms of environmental impact (Mirabella and Allacker, 2017). This drawback can be overcome by coupling MFA with LCA, thus quantifying environmental impacts related to the use of products and services within the city through the entire life cycle, including outside the city boundaries, hence applying a consumption-based perspective. However, both MFA and LCA are resource-intensive modelling approaches that require extensive data on consumption and production of products and goods, as well as detailed information about waste management at city level, which is often a challenge to acquire.

Another approach targeting the limitations of the GHG Protocol and MFA coupled with LCA, is input-output (IO) models. In these models, aggregated sector-level monetary flows, typically more readily available at city level, are used in combination with emission intensities that quantify GHG emissions per monetary flow attributable to each sector. Multi-region IO (MRIO) models, which integrate trade mechanisms within and across sectors between countries, can, thus, assess the climate change footprints (CCFs, often referred to as carbon footprint) of cities (Ivanova et al., 2017; Wiedmann et al., 2021; Zheng et al., 2021). The most advanced study applying such an approach is currently the study by Moran et al. (2018), who estimated CCFs for 13,000 cities in 2015 by downscaling national or subnational footprints to the level of individual cities by considering population and purchasing power. Although extensive, the work of Moran et al. (2018) is limited by its lack of geographical and temporal differentiations. Not all countries publish annually updated national input-output tables, which form the basis of their assessment, and the model used to identify urban areas is only updated every 10–15 years. Misrepresentation of rapidly evolving urban landscape is challenging to evaluate under such conditions. Additionally, the presented model relies on national statistics on urban vs. rural spending patterns, hence assuming that consumption trends are uniform across cities within a country. As demonstrated by the work of González-García and Dias (2019), cities in the same country can have markedly different consumption patterns and associated climate change impacts.

Existing assessments of city CCFs thus bear two major limitations that hamper their use by local decision makers: dependence on resource-intensive modelling, which may be challenging for local authorities to use (e.g. MRIO modelling), and reliance on significant amounts of data, often not readily available for a given city and year (e.g. MFA-LCA). The work of Baur et al. (2015b) exemplifies a simple approach that indeed overcomes the modelling challenges outlined in the previous sections. In that work, greenhouse gas emissions are estimated for European cities using multiple regression models (MLRs) with two variables, namely household size and population density. However, Baur et al. (2015b) only cover territorial emissions and thus disregard the potentially overshadowing emissions embodied in commodities, as established in the above. Additionally, while data on household size may be consistently available for cities within Europe, access to this type of data at city level in developing regions is likely limited. Inconsistency in data availability compromises the possibility to benchmark estimated CCFs – both spatially, i.e. across more cities for a single year, and temporally, i.e. for a single city across several years.

Hence, there is yet a need for a simple, albeit scientifically-robust, and reproducible approach allowing local decision makers to gauge and monitor cities' consumption-based CCF for a specific year without requiring comprehensive calculations and access to extensive datasets. In the current study, we address this gap and present a parsimonious screening tool, enabling quantitative assessment of consumption-based CCFs at city level. As a proof of concept, we apply it to 949 cities worldwide to estimate their CCFs. Beyond discussing the performance of the screening tool, we explore how the cities' footprint result relate to the global reduction targets, as outlined by the Paris Agreement.

2. Material and methods

To develop a screening tool that enables an assessment of city CCFs, results from existing bottom-up studies of cities are used to train multiple linear regression (MLR) models. With MLR models, independent variables, whose values are known, are used to predict the value of an unknown dependent value. MLR models can be an effective tool for creating predictive equations (Osborne, 2000). In the context outlined in Section 1, they can be particularly useful as the amount of necessary calculations is minimized and data requirements can be managed through the selection of the independent variables, as described further in Section 2.2.

Fig. 1 illustrates the overall methodology applied in the current study. In this work, the environmental impact potential is referred to as "climate change footprint", which is also commonly referred to as "carbon footprint". Climate change footprint is the impact assessment from emissions of all greenhouse gases (including non-carbon-based substances).

2.1. Step 1: Data collection

The first step of creating the MLR models was to collect all existing bottom-up studies of city CCFs. We used the search engine Web of Science (Clarivate, 2020) and only included peer-reviewed scientific literature (in English). Details on the search query and the studies included are available in Table S1 in Supporting Information. Finally, we applied a set of selection criteria, and identified 12 studies covering 34 cities that complied with all criteria, see Table S1 in Supporting Information. These 34 cities make up the so-called training set, used to develop the MLRs. The 34 cities are not evenly distributed geographically which will influence the representativeness of any predictions made with the hereof derived MLRs. To address this, the regional representativeness of the MLRs is investigated in Section 3.2 and possible bias in predictions is discussed.

2.2. Step 2: Evaluating possible drivers

The second step of the approach outlined in Fig. 1 was to identify city characteristics that could be potential drivers of CCF. Eleven possible drivers were found to be reported in past studies as having an important contribution to cities' CCF. Table 1 reports justifications for including each driver and highlighting any debate or contradicting conclusions regarding the driver found in literature. Additionally, the data requirements of each driver in terms of data availability and consistency was evaluated (See Table S2). This was done to keep the MLRs simple enough to ensure consistency between cities when applied. Each driver was scored on a scale of 1–3 for both data availability and consistency. This score is considered in Step 4 when selecting the best MLRs. Table S3 and S7 in Supporting Information provide an overview of the data used for each driver. Each driver was tested for correlation with other drivers based on Pearson's correlation coefficients. Since no formal rule exists on which value indicates a sufficiently strong correlation, a cautionary approach was taken, accepting no correlation higher than 0.6 to ensure as high independence between the variables as possible. For example, the variable Gross domestic product (GDP) and Population have a correlation coefficient of 0.914 and were thus not combined in any MLR. Correlation coefficients for all combinations of drivers can be found in Table S4 in Supporting Information.

2.3. Step 3 and 4: Developing and selecting predictive models

With 11 drivers as independent variables, 2047 possible combinations could be made to achieve regression models with the dependent

Table 1
Relevant and possible drivers of cities' CCF.

Possible driver	Justification	Driver previously investigated by
Population [capita]	Some of the world's largest cities in terms of population also have the largest carbon footprints, e.g. Seoul (South Korea), Guangzhou (China) and New York (USA). There are however plenty of examples of large cities having small footprints, e.g. Lagos (Nigeria).	Brown et al. (2008); Glaeser and Kahn (2010); Moran et al. (2018); Wang et al. (2014)
GDP adjusted for purchasing power parity [10^9 €] and [10^3 €/capita]	Increasing wealth may lead to increasing consumption, and thus increasing emissions, but could also lead to a shift toward environmentally friendly goods and energy efficient transport.	Moran et al. (2018); Wang et al. (2014); Wiedmann et al. (2021)
Area [km^2]	A larger area could – if population is not proportionally large – mean more square meters of living space per capita and longer transportation distances, affecting energy consumption for heating, cooling and fuels.	Baur et al. (2015a)
Annual average temperature; Annual average of daily minimum temperature; Annual average of daily maximum temperature [°C]	Studies comparing cities across continents and countries find no or weak correlation between impact and e.g. temperature. However, differences in temperature are often used as an explanation for differences in impact when comparing cities within a study.	Ivanova et al. (2017); Moran et al. (2018); Muñiz and Dominguez (2020); Singh and Kennedy (2015)
Population density [capita/km^2]	High population density has previously been found to have a decreasing effect on emissions from transportation. However, some studies find that areas with high population density have higher impacts as cities with high-density zones tend to have older and thus less energy-efficient buildings.	Baur et al. (2015a), (2015b); Kennedy et al. (2007); Moran et al. (2018)
Household (HH) median disposable income [10^3 €]	Income directly influences ability to consume and thus may increase emissions. However, as argued under purchasing power parity adjusted GDP, higher income can lead to a shift toward goods with lower impacts i.e. presence of an environmental Kuznets curve (David, 2004).	Ivanova et al. (2017); Kalmykova et al. (2016)
CO_2 intensity of electricity production in the city [kg CO_2-eq/kWh]	Electricity mix intensity intuitively influence the climate change impact of products produced locally. There could however be a rebound effect causing citizens with access to "cleaner" energy to increase energy consumption.	Ivanova et al. (2017); Wang et al. (2014)
Consumer price of electricity [€/kWh]	The price of electricity locally is likely to affect how much citizens consume. If electricity is cheap, people may consume more, thus increasing impact on climate change.	Kennedy et al. (2015)

variable "climate change impact". To narrow down this number, a set of rules were imposed step by step:

- Max. five independent variables to avoid overfitting (possible combinations: 1023)
- No correlated drivers combined (possible combinations: 372)
- All independent variables show significant contribution to the explanatory power of model ($p < 0.05$) (possible combinations: 19)

The 19 possible combinations are presented in Supporting Information, Table S5. The final selection among these models was based on evaluation against three criteria:

1. Availability and consistency of data. How available and consistent is the data needed as input? (Scored 1–3, where 1 is best and 3 is worst, cf. Table S2)
2. Adjusted r^2. Amount of variance in the sample explained by the model (cf. Table S5)
3. Q^2. Amount of variance in the sample predicted by the model (cf. Table S5)

With respect to Point 3 in the model validation, Q^2 was determined using a leave-one-out (LOO) cross-validation process (Xu and Goodacre, 2018) following Equation (1). A high coefficient indicates that the model has good internal predictive power.

$$Q^2 = 1 - \frac{PRESS}{TSS} \leftrightarrow 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y}_i^{-i}\right)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where:

PRESS = Predicted residual error sum of squares
TSS = Total sum of squares
n = Sample size
y_i = Reported total CCF for observation *i*
$\hat{y}_i^{(-i)}$ = Predicted CCF for observation *i*, when training without the *i*th observation
$\bar{y}$ Mean of y

Applying these three criteria to the 19 shortlisted regression models, three models were selected (see Table S5 for details). As the basis for the 19 regression models, i.e. the training set, the characteristics of the 34 cities covered by the 12 shortlisted studies described in Section 2.1 represent the applicability limits of the regression models. This means that results obtained for cities with any characteristic, e.g. population size, either higher or lower than that of the 34 cities, should be considered with caution as the validity of the models is then not ensured. The limits of the models' applicability are reported in Supporting Information, Table S6.

Additionally, an interval validation was performed to validate the models ability to predict impact results beyond the time period of the training set (1997–2016). The 34 cities were split into three time periods (1990–1999, 2000–2010, and 2010–2020). The first group was disregarded as it only contained three cities, hence yielding a too limited dataset to be used for this purpose. The second group (containing 18 cities) was used to train the regression models, which were then applied to predict impacts for the third group, containing 13 cities. The predicted results for the 13 cities and the reported CCF in the original studies are presented in Table S10.

We found that, for 10 of the 13 cities, the predicted impact deviated from the reported impact with less than 50% with at least one of the models. For the remaining cities, the deviation exceeded 100% with all three models. There is, however, no indication that the deviation increase as a function of time. The predicted impacts for Bilbao and Seville in 2016 (from the most recent study; González-García and Dias, 2019) deviated with less than 40% for all models. However, Mexico City and New York City were found to have markedly overestimated impacts. This is likely due to a geographical bias inherent to the dataset (due to limited data availability), which is further discussed in Section 3.2.

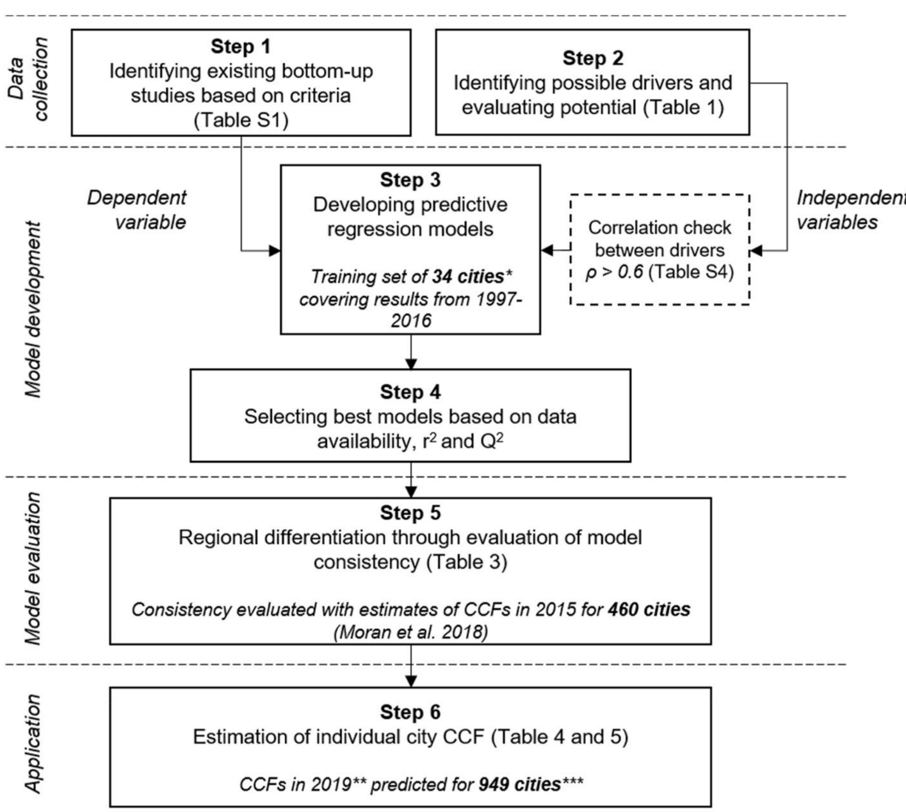
Additionally, the regression models were evaluated on their consistency with previous work. The CCF predictions were compared to modelled values for 460 cities (Moran et al., 2018) covering the year 2015. When the 95% confidence interval (CI) of the MLR prediction overlapped with the 67% CI reported by Moran et al. (2018), the two results were deemed consistent. A full list of the 460 cities and the predicted CCF for these is documented in Table S11 in Supporting Information. The knowledge gained from this consistency evaluation was furthermore used to guide a regional differentiation in the model application. All three models were applied to the 460 cities. The model that ensured consistency between predicted CCF and the modelled value reported by Moran et al. (2018) for the highest number of cities was identified as preferable. The three models were evaluated by world regions, defined as Africa, Western and Central Asia, South and Southeast Asia, East Asia, Oceania, South America, North America and Europe. Based on this statistical analysis, a preferred model, i.e. a model demonstrating the overall highest degree of consistency with the results obtained by Moran et al. (2018), was selected and recommended for each region.

One important assumption behind this step is the reliability of the results by Moran et al. (2018). Moran et al. (2018) address several points of uncertainty in their work, including assumptions regarding consumption patterns in rural and urban areas. They have attempted to account for these uncertainties with sensitivity analysis and uncertainty margins. Thus, in the absence of better comparative ways, it was deemed a useful exercise to test the precision of our approach; considering the very different approaches undertaken in the current study and in Moran et al. (2018), such a comparison can also provide clues as to the accuracy of the assessment.

3. Results and discussion

3.1. Presentation of predictive models

Based on Steps 1–4 outlined in Fig. 1, 19 MLR models were developed and using the three criteria, the models in Eqs. (2)–(4) were selected as the three strongest models for predicting CCFs for cities. Table 2 presents the central statistical characteristics of the regression models.



* The characteristics of the 34 cities represent limitations of the regression models' applicability. See Table S6 in Supporting Information 1.

** Where data for 2019 was not available, the most recent year was used, the oldest data used is from 2016.

*** Of the 949 cities, 242 have one or more characteristic outside the limits defined by the training set.

Fig. 1. Overview of the six methodological steps through four phases of data collection (Step 1 and 2), model development and selection of statistically strong multiple regression models (Step 3 and 4), evaluation of the model consistency (Step 5) and application, where CCF is predicted for 949 cities (Step 6).

Table 2
Statistics of the regression models.

Model GPDGC *Log(CCF)*		Model PGC *Log(CCF)*		Model APDGC *Log(CCF)*	
Intercept	14.96***	*Intercept*	0.44	*Intercept*	1.88.
Log(GDP)	1.12***	*Log(Pop)*	1.10***	*Log(area)*	1.12***
GDP/cap	−0.02***	*GDP/cap*	0.02**	*GDP/cap*	0.02**
Log (Pop_dens)	−0.26**			*Log (Pop_dens)*	0.88***
Adjusted R-squared	0.9153	*Adjusted R-squared*	0.9055	*Adjusted R-squared*	0.9262
P-value	<2.2e-16	*P-value*	<2.2e-16	*P-value*	<2.2e-16
Q-squared	0.900	*Q-squared*	0.891	*Q-squared*	0.908

Significance: '.' = p-value < 0.1, '*' = p-value < 0.05, '**' = p-value < 0.01, '***' = p-value < 0.001.

Model GPDGC:

$$log(CCF) = 14.96 + 1.12 \cdot log(GDP) - 0.26 \cdot log(Pop\_density) - 0.02 \cdot GDP/cap \tag{2}$$

Model PGC:

$$log(CCF) = 0.44 + 1.10 \cdot log(Pop) - 0.02 \cdot GDP/cap \tag{3}$$

Model APDGC:

$$log(CCF) = 1.88 + 1.12 \cdot log(Area) + 0.88 \cdot log(Pop\_density) + 0.02 \cdot GDP/cap \tag{4}$$

… where:

CCF = The total climate change footprint in tons CO_2-eq per year
GDP = The gross domestic product of the city in billion euros adjusted for purchasing power parity (PPP)
Pop_density = The population density of the city in persons per km^2
GDP/cap = The gross domestic product per capita in the city in thousands euros adjusted for PPP
Pop = The population of the city in persons
Area = The land covered by the city in km^2

For the three models, GPDGC, PGC and APDGC, the main drivers of climate change impact is GDP, population size and area, respectively. With these models, an increase in the three main variables has an increasing effect on the predicted total climate change impact for a city. Firstly, one possible interpretation is that wealth, and hence ability to consume, influences climate change impacts. This is aligned with previous observations made at national level, e.g. (Hertwich and Peters, 2009) who reported higher CCF for developed countries than for developing countries. Secondly, as Table 2 shows, the size of the city (both in terms of inhabitants and land occupation), influences the total CCF, suggesting that larger and more populous cities tend to have higher impacts.

With respect to the influence of GDP per capita, it can be observed that the CCF decreases with higher GDP per capita with the model GPDGC, while the opposite is visible with the models PGC and APDGC. As described by Verma and Kandpal (2021), higher GDP per capita may provide opportunity for technological innovation, potentially favoring more low-carbon technologies. However, as GDP per capita often reflects the affluence of the population and thus its ability to consume, a trade-off occurs with increasing wealth having both an increasing and a decreasing effect on climate change impacts, the net result of which depends on the city assessed (Verma and Kandpal, 2021). In developing regions, increasing wealth may lead to industrialization as well as increased ability to consume, thus increasing climate change impact dramatically through direct emissions from fuel combustion and indirect emissions embodied in consumption. In developed countries, increasing wealth may stimulate investments in climate change mitigating technologies, e.g. decarbonization of the energy mix, leading to overall decrease of CCF. On the other hand, wealth has been shown to be positively associated with increased political interest (Gonzalez-Gorman et al., 2019), and a higher GDP per capita could thus also be linked to a population demanding more political action towards mitigating climate change. For instance, a United Nations survey recently found that high-income countries showed the second highest level of support towards climate action behind the small island developing states, for which climate change impacts are already dire (UNDP, 2021).

Like GDP per capita, increasing population density has a contrasting effect on the CCF depending on the three models considered (GPDGC, PGC and APDGC). The work of Kennedy et al. (2007) and Muñiz and Dominguez (2020) indicate that while higher population density may have a decreasing effect on transportation-related GHG emissions, it can be associated with higher housing-related emissions depending on the geographical context. For example, in European cities, high-density areas tend to have an older and less energy-efficient building stock associated with a higher CCF (Muñiz and Dominguez, 2020). It means that a high population density in a city may not be directly linked to higher impacts, but rather indirectly, through the era in which the city was primarily erected, as this time period may explain part of the energy efficiency performances of the building stock. Finally, high-density areas may increase the citizens' access to services such as restaurants, entertainment and retail, thereby stimulating consumption and hence the CCF per capita. As for wealth, the resulting effect from population density on CCF will therefore depend on the city assessed.

It should be noted, that these interpretations of the relationship between total CCF and population density and GDP per capita are just some possible explanations, and that a statistically significant relationship between a dependent and independent variable in a MLR does not imply a causal relationship. The three MLRs are so far limited to estimating CCF, but could potentially be extended to other environmental impacts as well. There is, however, a lack of bottom up-studies considering other impacts than climate change, and as the predictive models are built and trained with bottom up-studies, this is a barrier. The MLRs are valid as long as the inherent underlying driver mechanisms remain constant. For example, if the building stock of European cities undergoes energy renovation in the coming years, it may be possible to partly decouple high population density from high CCFs as emissions associated with heating will be reduced.

3.2. Regional differentiation of model applicability (Step 5)

As described in Section 2.3, the performance of the three regression models was evaluated against previously estimated CCFs for a set of 460 cities for the year 2015 (using results from (Moran et al., 2018)). With the model GPDGC, the predicted CCFs was found to be consistent with previously estimated results for 343 out of 460 cities. With models PGC and APDGC, consistency was found for 367 and 382 out of 460 cities, respectively.

Table 3 shows that for South and Southeast Asia, South America and Europe the number of cities, for which a model is consistent with existing findings, varies markedly between models. This difference is likely related to the drivers behind the CCF, which vary from region to region (C40, 2018). While model GPDGC is the model most consistent with the study by Moran et al. (2018) for cities in North America and South America (91.8% and 80.8%, respectively), it is the model with poorest prediction for cities in Europe, where model APDGC gives consistency for the highest share of cities (97.7%). This may be explained by the fact that GHG emissions related to transportation are

Table 3
Overlap between the 95%-CI for each model and test set (Moran et al., 2018).

	Overlap between GPDGC predicted impact and test set impact	Overlap between PGC predicted impact and test set impact	Overlap between APDGC predicted impact and test set impact
Africa (N = 12)	5 (41.7%)	5 (41.7%)	6 (50.0%)
Western and Central Asia (N = 34)	26 (76.5%)	28 (82.4%)	26 (76.5%)
South and Southeast Asia (N = 45)	34 (75.6%)	15 (33.3%)	27 (60.0%)
East Asia (N = 107)	69 (64.5%)	94 (87.9%)	94 (87.9%)
Oceania (N = 8)	6 (75.0%)	6 (75.0%)	5 (62.5%)
South America (N = 26)	21 (80.8%)	12 (46.2%)	18 (69.2%)
North America (N = 98)	90 (91.8%)	82 (83.7%)	80 (81.6%)
Europe (N = 129)	92 (71.3%)	125 (96.9%)	126 (97.7%)

less dominant in European cities (only 3%) than in North American and South American cities (C40, 2018). Model GPDGC thus performs well for cities, where high population density can be regarded as a good indicator of how car-dependent the population is (e.g. in the US). In contrast, the APDGC model is a strong model for older cities like those in Europe, where population density indirectly represents a less energy-efficient building stock.

All three models ensure relatively high consistency for cities in East Asia. Of the 34 cities in the training set, nine are located in China, which together with Mongolia, Taiwan, North and South Korea, and Japan make up the East Asia region. Similarly, seven of the 34 cities are located in Australia (belonging to the region Oceania). Having just two countries (China and Australia) representing nearly half of the cities used to train the regression models, will possibly ensure higher accuracy for cities in these countries. Finally, there are regions that are very poorly represented in the training set, e.g. Africa (represented with one city) and North America (represented with three cities), and regions which are not at all represented in the training set, e.g. South America, Western and Central Asia, and South and Southeast Asia. This is due to a lack of available bottom-up studies on cities in these regions. Future studies should aim to cover these regions, which could greatly improve the representativeness and predictive power of the regression models.

It is plausible that the high level of consistency observed between the previously estimated CCFs for the 460 cities (Moran et al., 2018) and the models applied in this work is due to both approaches being tied to the economic profile of the city. Moran et al. (2018) estimated CCFs for cities by downscaling national CCFs obtained from the Eora global MRIO (Kanemoto et al., 2016; Lenzen et al., 2012). The models presented in this work shows the least consistency with previously obtained results for cities in Africa. Although Eora covers 187 countries, only 74 have a corresponding national input-output table available, while a proxy table is constructed for the remaining 113 countries by combining macro-economic data with a template structure based on the average of tables for Australia, Japan and the United States (Lenzen et al., 2012). Only three African countries (Kenya, South Africa and Mauritius) publish national input-output tables, while IO tables for the rest of Africa rely on assumptions and modelling. Thus, CCFs estimated by Moran et al. (2018) for cities in African countries could bear important uncertainties, decreasing the relevance of comparing the results in this study with those from Moran et al. (2018) for this region.

3.3. Estimating climate change footprint for 707 cities (Step 6)

Based on Table 3, we identified the model that is most consistent with previous work in each region and applied the selected models to a set of 949 cities applying data for the most recent year available (2016–2019). Of these, 242 were excluded from further analysis because they have one or more city characteristics that lie outside the range stipulated by the characteristics of the 34 cities in the training set. Their results can be found in Supporting Information, Table S14 (cities highlighted in yellow) since they may still be relevant for comparative purposes once future research manages to expand the applicability of the MLRs.

It should be noted, that the purpose of this work was to propose models that can support the assessment of consumption-based emissions. The application of the MLRs to 707 cities should be seen as a proof of concept and does in no way represent an exhaustive list of cities that the models could potentially be applied to. Currently, the necessary data is however not publicly available for all cities worldwide and certain regions are underrepresented in the 707 cities. However, as the models presented in this work is intended for local decision makers who in all probability have access to this type of data on the city they manage, this is not considered to be a vital flaw in the models.

The top 10 list of cities in terms of total and per capita CCF is presented in Figs. 2 and 3, respectively (the bottom 10 cities are shown in Table S15). The purpose of highlighting the cities with the highest emissions is to identify the cities that are currently responsible for the largest share of global urban emissions, and hence which cities have the influence and potential to reduce the largest share of global emissions.

Of the remaining 707 cities, the city with the highest total CCF is Beijing, China, with a CCF of 422 [95% confidence interval, CI95: 294; 606] Mt CO_2-eq/yr. Chinese cities also rank in the top in terms of per capita CCF in Asia, where Beijing with 19.6 [CI95: 13.7; 28.1] t CO_2-eq/capita/yr is the city with the highest CCF per capita. Chinese cities have per capita CCFs comparable to cities in both Europe and North America (averages of 11.4, 9.1 and 11.2 t CO_2-eq/capita/yr, respectively), which is a testament to the rapid economic development that China has undergone in the past three decades (Tian et al., 2014). It is clear that these results are largely driven by the increase in the affluence of the Chinese population and, along with this, the evolution of its consumption patterns.

Among all the studied cities, Australian cities have the highest per capita CCF. In Geelong, located in the state of Victoria, inhabitants are estimated to have a CCF of 25.9 [CI95: 18.6; 35.9] t CO_2-eq/capita/yr. The highest per capita CCF of Australian cities is found in cities that are generally smaller in terms of population and have low population density. Model GPDGC is applied to cities in Oceania (only Australia and New Zealand included), and as described in Section 3.1 and presented in Table 2, a high population density will thus decrease the predicted CCF, thus explaining why higher CCFs are predicted for the less dense cities of Australia.

The cities with the lowest per capita CCF are found in Colombia, Kenya and Senegal. The Colombian cities have an average per capita CCF of 6.5 t CO_2-eq/capita/yr with the city Armenia having the lowest predicted CCF in the entire assessed set of cities with 4.3 [CI95: 2.5; 7.3] t CO_2-eq/person/yr. Colombian cities have some of the lowest GDP of the 707 cities, and model GPDGC will thus predict lower total CCF. As the Colombian cities are not correspondingly small in terms of population size, the per capita CCF can be expected to be low. Additionally, the Colombian cities are densely populated and with the model GPDGC this further contributes to a lower CCF, as described in Sections 3.1 and 3.2. For both Kenya and Senegal, only one city is included, namely the capital cities Nairobi and Dakar, where the CCF per capita is estimated to be 5.12 [CI95: 2.6; 10.2] t CO_2-eq/person/yr and 5.25 [CI95: 2.6; 10.4] t CO_2-eq/person/yr, respectively. Both Nairobi and Dakar have very low per capita GDP (6720 and 7140 euros, respectively), which will contribute to a low per capita CCF with model APDGC.

Comparing the results in Fig. 2 to previously estimated CCFs, it is observed that especially cities in the United States and Canada are estimated somewhat lower in this work. In previous studies, e.g. Moran et al. (2018), Canadian and US cities have been assessed as metropolitan regions and thus represented a larger, less dense urban area, while the results from the current study for US and Canada in Figs. 2 and 3 represent only the core urban area. For example, for Los Angeles Moran et al. (2018) report a population of 13,482,000 inhabitants (covering the total Los Angeles-Long Beach-Anaheim area), while only the central area of Los Angeles and its 4,000,000 inhabitants is considered in the present study.

The top ten European cities by CCF per capita are all located in countries that have some of the highest GDP per capita in Europe (United Kingdom, the Netherlands, Sweden, France, Norway, Germany and Finland). The bottom 10 European cities by CCF per capita (see Supporting Information, Table S15) are similarly located in countries that have some of lowest GDP per capita in Europe (Bulgaria, Romania, Croatia, Poland, Hungary). This finding supports the work of Lorek et al. (2021) who found that the top 10% richest in Europe have a carbon footprint of more than twice the size of the bottom 50%.

In the set of 707 cities there is an overrepresentation of cities in developed countries. The assessed set contain only a few cities in Africa, and both Asia, Oceania and South America are represented by only a few countries that are not necessarily representative of the entire region. Cities in these underrepresented regions are expected to have low per capita CCFs, likely lower than any of the 707 cities assessed.

The results presented in this section demonstrate that with only three variables, namely population, GDP and area of a city, it is possible to estimate consumption-based CCF for a city. As the MLRs are not restricted to a single year, the latest available data could therefore be used for each individual city, hence ensuring the highest possible degree of relevance. The models are not hindered by temporal availability of data and it is thus not necessary to perform projections of outdated data to fit with a specific year, which may increase the uncertainty of the so obtained results. As shown in Table S12, all necessary data on the cities was available in either national or regional statistical databases, thus demonstrating the convenience and flexibility of the MLRs, without comprising on accuracy as illustrated in Section 3.2.

3.4. Evaluating the impact contribution of cities

To evaluate cities' overall potential of climate change mitigation, an urban contribution factor (UCF) is estimated for each country. The UCF is estimated for a country by dividing the (in this study) covered share of total national CCF by the (in this study) covered share of total national population; see Equation (5). The total national climate change impacts were extracted from the Eora MRIO model (Kanemoto et al., 2016; Lenzen et al., 2012) and the total national population was taken from (United Nations, 2019).

$$UCF = \frac{\sum_{i=city} CCF_{i,j}}{CCF_{country,j}} \Bigg/ \frac{\sum_{i=city} Population_{i,j}}{Population_{country,j}} \tag{5}$$

where:

$\sum_{i=city} CCF_{i,j}$ is the sum of the covered cities' CCF within a country, j

$\sum_{i=city} Population_{i,j}$ is the sum of the covered cities' population within a country, j

For the example Australia, the pool includes seven assessed cities. The sum of their CCF is 264 Mt CO_2 eq./yr., or equivalent to 52% of Australia's total CCF of 507 Mt CO_2 eq./yr (Kanemoto et al., 2016; Lenzen et al., 2012). The total population of the seven cities is 14.4 million people or equivalent to 57% of Australia's total population of 25.4 million people (United Nations, 2019). With Equation (5), the UCF for Australia is thus calculated to be 0.93. This number provides an indication of whether urban life is more or less climate change impact

	North America GPDGC		South America GPDGC		Oceania GPDGC		Asia APDGC		Europe APDGC		Africa APDGC	
	City	Impact (Mt CO_2 eq/yr)	City	Impact (Mt CO_2 eq/yr)	City	Impact (Mt CO_2 eq/yr)	City	Impact (Mt CO_2 eq/yr)	City	Impact (Mt CO_2 eq/yr)	City	Impact (Mt CO_2 eq/yr)
1	Mexico City[a], MX	199 (139;285)	Sao Paulo[b], BR	149 (94;235)	Melbourne[a], AU	78 (64;95)	Beijing[a], CN	422 (294;606)	London[a], UK	172 (117;254)	Lagos[b], NG	173 (93;320)
2	Monterrey[a], MX	67 (55;83)	Lima[b], PE	107 (75;153)	Sydney[a], AU	75 (60;94)	Chongqing[a], CN	338 (234;488)	Istanbul[a], TR	145 (102;206)	Johannesburg[b], ZA	40 (25;65)
3	Guadalajara[a], MX	44 (33;58)	Santiago[a], CL	84 (65;109)	Brisbane[a], AU	35 (29;42)	Seoul[a], KR	227 (160;323)	Paris[a], FR	140 (95;206)	Tshwane[b], ZA	35 (22;55)
4	Houston[b], US	32 (23;44)	Bogota[a], CO	72 (53;98)	Perth[a], AU	31 (23;42)	Tianjin[a], CN	194 (150;251)	Madrid[a], ES	61 (48;78)	Abidjan[b], CI	33 (19;59)
5	Toronto[b], CA	29 (23;38)	Rio de Janeiro[b], BR	68 (45;102)	Auckland[a], NZ	19 (16;23)	Osaka[a], JP	191 (14;252)	Ankara[a], TR	56 (47;67)	Cape Town[b], ZA	33 (21;52)
6	Chicago[b], US	28 (19;42)	Quito[b], EC	30 (21;42)	Adelaide[a], AU	18 (14;21)	Guangzhou[a], CN	168 (126;223)	Ruhr[a], DE	40 (34;48)	Ekurhuleni[b], ZA	31 (20;48)
7	Phoenix[b], US	24 (19;29)	Medellin[a], CO	21 (14;30)	Gold Coast[a], AU	8 (6;10)	Jakarta[b], ID	165 (124;219)	Berlin[a], DE	39 (32;49)	Durban[b], ZA	28 (18;45)
8	San Antonio[b], US	21 (18;26)	Curitiba[b], BR	17 (12;23)	Newcastle[a], AU	6 (5;8)	Bangkok[b], TH	135 (92;200)	Athens[a], GR	38 (32;46)	Nairobi[b], KE	23 (12;46)
9	Dallas[b], CA	17 (13;23)	Cali[a], CO	17 (12;23)	Christchurch[a], NZ	5 (4;7)	Wuhan[a], CN	132 (106;165)	Rome[a], IT	34 (29;42)	Dakar[b], SN	7 (4;15)
10	Juarez[a], MX	16 (12;25)	Bucarama[a], CO	11 (8;15)	Canberra[a], AU	5 (4;7)	Nagoya[a], JP	107 (86;132)	Amsterdam[a], NL	34 (25;46)	-	-

[a]Metropolitan area
[b]Urban center

Fig. 2. Heat map of predicted CCF for the top 10 cities in North America (US, Canada and Mexico), South America (Chile and Colombia), Oceania (Australia), Asia, Africa (South Africa, Nigeria, Kenya, Senegal and Côte d'Ivoire) and Europe. 95% confidence intervals for the predictions are given in parenthesis. Color coding: from red, through orange and yellow to green: decreasing CCF values.

	North America GPDGC		South America GPDGC		Oceania GPDGC		Asia GPDGC, PGC, APDGC		Europe APDGC		Africa APDGC	
	City	Impact ($t\ CO_2$ eq/yr)	City	Impact ($t\ CO_2$ eq/yr)	City	Impact ($t\ CO_2$ eq/yr)	City	Impact ($t\ CO_2$ eq/yr)	City	Impact ($t\ CO_2$ eq/yr)	City	Impact ($t\ CO_2$ eq/yr)
1	Villahermosa[a], MX	17.0 (11.7;24.6)	Concepcion[a], CL	17.5 (12.7;23.9)	Geelong[a], AU	25.9 (18.6;35.9)	Beijing[a], CN	19.6 (13.7;28.1)	London[a], UK	16.7 (11.3;24.6)	Tshwane[b], ZA	9.8 (6.2;15.4)
2	Jacksonville[b], US	16.9 (12.7;22.5)	Rancagua[a], CL	12.6 (8.5;18.6)	Wollongong[a], AU	24.3 (18.0;32.9)	Guangzhou[a], CN	17.6 (13.2;23.4)	Amsterdam[a], NL	16.3 (12.1;21.9)	Cape Town[b], ZA	7.9 (5.1;12.3)
3	Oklahoma City[b], US	16.8 (12.3;22.9)	Sao Paulo[b], BR	12.5 (7.9;19.7)	Gold Coast[a], AU	22.8 (17.9;29.0)	Hangzhou[a], CN	15.7 (12.5;19.6)	Stockholm[a], SE	15.9 (12.0;21.0)	Ekurhuleni[b], ZA	7.9 (5.1; 12.3)
4	Huntsville[b], US	15.0 (10.0;22.6)	Santiago[a], CL	11.7 (9.1;15.1)	Newcastle[a], AU	22.1 (17.0;28.8)	Jakarta[b], ID	15.7 (11.8;20.9)	Paris[a], FR	15.2 (10.3;22.5)	Durban[b], ZA	7.6 (4.8;12.1)
5	Columbus[b], US	14.9 (10.0;22.2)	Lima[b], PE	11.3 (7.9;16.1)	Perth[a], AU	21.6 (16.1;28.9)	Dubai[b], AE	15.6 (11.5;21.3)	Oslo[a], NO	13.8 (10.5;18.0)	Johannesburg[b], ZA	7.6 (4.7;12.2)
6	Kansas City[b], US	14.7 (10.7;20.3)	Villavicencio[a], CO	11.1 (7.4;16.7)	Brisbane[a], AU	20.2 (16.8;24.2)	Bangkok[b], TH	15.5 (10.5;22.9)	Guildford[a], UK	13.7 (9.4;19.8)	Lagos[b], NG	7.2 (3.9;13.4)
7	Monterrey[a], US	14.6 (11.9;18.0)	Quito[b], EC	10.6 (7.5;15.0)	Melbourne[a], AU	18.2 (14.9;22.3)	Nanjing[a], CN	15.0 (11.4;19.5)	Dusseldorf[a], DE	13.3 (9.8;18.1)	Abidjan[b], CI	6.2 (3.5;10.9)
8	Memphis[b], US	14.2 (10.9;18.6)	Rio de Janeiro[b], BR	10.3 (6.8;15.5)	Canberra[a], AU	17.4 (13.0;23.2)	Sebuk[a], KR	14.9 (11.4;19.5)	Helsinki[a], FI	13.3 (10.7;16.6)	Dalar[b], SN	5.2 (2.6;10.4)
9	Phoenix[b], US	14.1 (11.5;17.4)	Valparaiso[a], CL	9.8 (7.0;13.7)	Sydney[a], AU	16.5 (13.2;20.7)	Wuhan[a], CN	14.6 (11.7;18.3)	Frankfurt[a], DE	13.3 (9.9;17.9)	Nairobi[b], KE	5.1 (2.6;10.2)
10	Virginia Beach[b], US	14.1 (10.4;18.9)	Bucaramanga[a], CO	8.8 (6.3;12.2)	Adelaide[a], AU	15.1 (12.5;18.4)	Ningbo[a], CN	14.5 (12.0;17.7)	Stuttgard[a], DE	13.2 (9.8;17.7)	-	-

[a]Metropolitan area
[b]Urban center

Fig. 3. Heat map of predicted CCF per capita for the top 10 cities in North America (US, Canada and Mexico), South America (Chile and Colombia), Oceania (Australia), Asia, Africa (South Africa, Nigeria, Kenya, Senegal and Côte d'Ivoire), and Europe. 95% confidence intervals for the predictions are given in parenthesis. Color coding: from red, through orange and yellow to green: decreasing CCF values.

intensive than rural life in Australia. If the UCF is below 1, the urban areas can be interpreted as climate change impact-wise preferable to suburban and rural areas within the country. It should however be noted that since not all cities are covered, the UCF is a merely an indication based on the available data. It is entirely possible that if all urban areas were considered, the UCF would be higher or lower for a given country.

From Fig. 4, it can be observed that for some countries, cities generally have lower climate change impact intensities than suburban or rural living, e.g. Australia (UCF = 0.92, CI95: 0.73; 1.15), Canada (UCF = 0.49, CI95: 0.38; 0.64), and the United States (UCF = 0.52, CI95: 0.37; 0.76). In contrast, there are countries where cities account for a larger share of impact than the share of the population that they accommodate, e.g. China (UCF = 1.68; CI95: 1.27; 2.24), Colombia (UCF = 1.64, CI95: 1.27; 2.24), and Kenya (UCF = 3.57, CI95: 1.79; 7.11). It is notable that countries in the former group are "developed economies", while countries in the latter group are all "developing economies" as classified by the United Nations (UN, 2022). In developing countries, urbanization is often linked to a large divide between urban and rural areas, which is recognized as one of the major differences between urbanization in developing and developed countries (Yuan et al., 2020). The urban-rural income gap is an example of such divide, which is particularly visible in China, where the urban-rural income gap is indeed recognized as one of

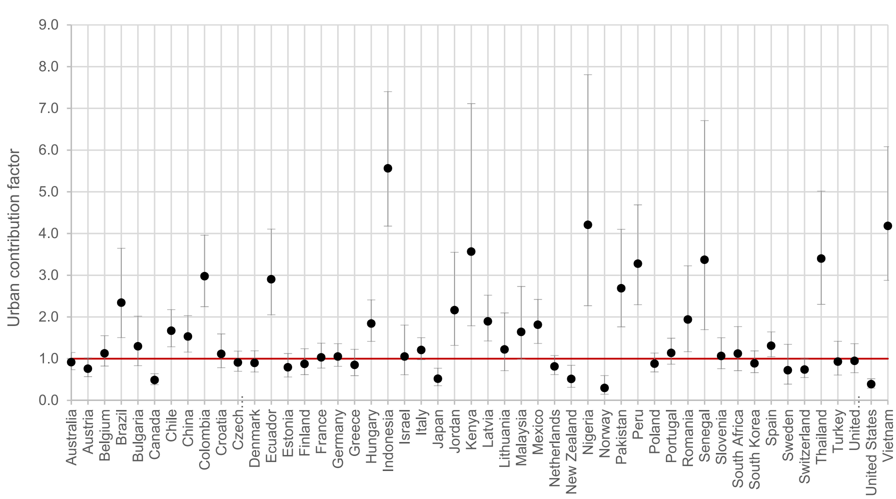


Fig. 4. Urban contribution factor (UCF) estimated for each country by dividing the covered share of total national CCF by the covered share of total national population. If below 1, urban areas within a country can be interpreted as preferable in terms of climate change impact intensity to suburban and rural areas within the country.

the most severe cases globally and has only increased over time (Yuan et al., 2020). Since ability to consume is inherently decisive for a high consumption-based CCF, it may thus be expected that in developing countries urban areas will have higher impacts than non-urban areas and urban areas will hence appear to be less environmentally preferable, although the difference mostly reflects large differences in standards of living between the cities and the rural areas. This illustrates the importance of considering social as well as environmental sustainability. If non-urban living is associated with poverty and lack of social protection it should not be considered a favorable alternative in spite of lower per capita CCF. Finally, it should be noted that although the considered cities in Colombia and Kenya only accommodate a small share of the population relative to the share of CCF that they are responsible for, CCF per capita is not on average high compared to cities in other assessed countries.

From Fig. 4 it is observed that the sum of CCFs for Chile, Peru and Jordan is very high and in fact close to the total national CCF. This likely an overestimation due to a lack of representativeness in the regression models as the training set for the MLRs did not include any cities from Chile, Peru or Jordan, due to no bottom-up studies being available for these regions. As mentioned in Section 3.3, some regions are not covered sufficiently yet, e.g. Africa, South America, and Southeast Asia, which leaves uncertainty in both the current and potential future impacts of cities in these regions. Indeed, the current knowledge on cities' climate change impact is predominantly based on Western perspectives and the lack of knowledge on environmental impacts in these regions is a challenge for sustainable cities (Nagendra et al., 2018). While today these regions are not dominant contributors to global climate change impacts, it is expected that with the projected growth in population and affluence, these regions (e.g. India) will be major contributors in the future. If these regions are investigated further, the models presented in this work could be fine-tuned and extended to increase robustness in the assessment of cities outside of North America, Europe and China.

Although Australia, the United States and Canada all have relatively low UCF, the cities in these countries generally have high per capita CCFs. As shown in Section 3.3, Australian cities are found to have the highest per capita CCFs in the assessed sample of cities. Thus, although urban areas have lower climate change impacts compared to the rest of Australia, it is not meaningful to consider these as environmentally sustainable given their high per capita CCFs. To provide a meaningful estimate of which cities that can potentially be considered as sustainable, it is imperative that the relative measure of the UCF is supplemented with an absolute measure, using a boundary for when per capita CCFs are not only lower, but low enough (see Section 3.5).

3.5. Aligning cities with the Paris Agreement

In Fig. 5, CCFs per capita are compared to the global pathways limiting global warming to 1.5 °C and 2 °C above preindustrial levels presented by the IPCC (Rogelj et al., 2018). These pathways provide an annual global budget that the total anthropogenic GHG emissions should respect to ensure that global warming is limited to 1.5 °C or 2 °C above preindustrial levels. For example, if global warming should be limited to 1.5 °C, the annual global GHG emissions should not exceed 27.9 Gt CO_2 eq./yr. by 2030 (Rogelj et al., 2018). To assign a share of this global budget to one city, an egalitarian approach is applied where all human individuals are given equal rights and thus the same share, i.e. the global budget of 27.9 Gt CO2 eq./yr. is divided by the projected global population in 2030 (United Nations, 2019) of 8.5 billion people. This gives each individual an allowable budget of 3.3 t CO_2 eq./capita/yr., which can then be multiplied by the population of a city to obtain the city's share. Although applying an egalitarian approach when sharing the global safe environmental operating space (i.e. the space within which humans can operate without jeopardizing the ecological stability of the Earth system) is one of the most common approaches (Bjorn et al., 2020), it is inherently an ethical choice. Another common approach is "Grandfathering", where the share assigned to an individual is proportional with environmental impact in a reference year (Bjorn et al., 2020). With this approach, cities or countries with historically high impacts will be assigned a larger share. In this study, owing to the illustrative purpose of providing a benchmark against the global carbon budget, only the egalitarian approach recommended by Ryberg et al. (2020) was followed, although other approaches may be applied to perform sensitivity analyses.

The pathways are scaled to the per-capita level in 2020 and 2030 (using global demographic historical data and projections; United

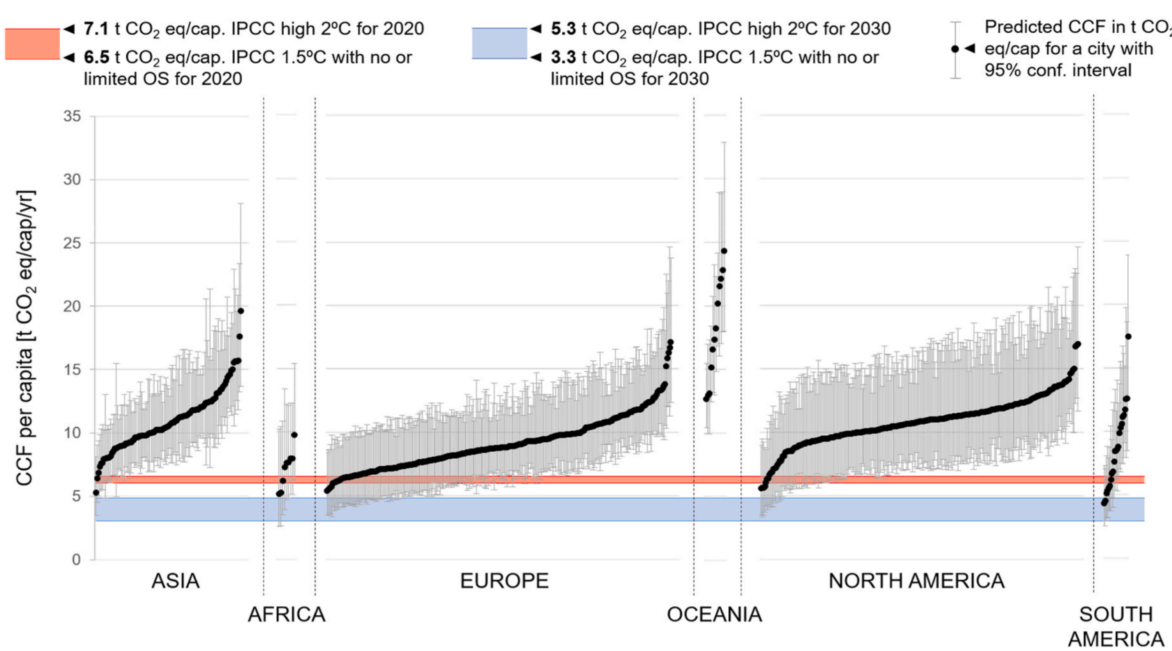


Fig. 5. Comparing climate change impact normalized per capita in t CO_2-eq/yr to the IPCCs global pathways to limiting global warming to 1.5° and 2° for 2030 with no or limited overshoot (OS). The global pathways are downscaled by dividing the total boundary with the global population. Error bars indicate 95%-confidence intervals for the CCF prediction.

Nations, 2019). The 1.5 °C and 2 °C boundaries for 2020 were scaled to 6.5 and 7.1 t CO_2-eq/capita/yr, respectively, and to 3.3 and 5.3 t CO_2-eq/capita/yr in 2030. The predicted CCF in t CO_2-eq/capita/yr for all of the cities are then compared to the boundaries for 2020 and 2030.

Of the 707 cities, only 74 cities have their mean predicted value below the 2 °C boundary in 2020. The majority (48 cities) of these 74 cities are found in Europe, with Mexican and Colombian cities (11 and 9 cities, respectively) making up the rest of the cities below the 2 °C boundary in 2020. For 370 cities it is, however, possible that their per capita CCF is within the 2 °C boundary in 2020 if the uncertainty of the prediction, i.e. 95% confidence intervals, is considered. Of the 48 cities in Europe with a mean predicted value below the 2 °C boundary in 2020, French and Polish cities tend to dominate. Electricity production in Poland is highly reliant on coal (Brauers and Oei, 2020), and in 2019 Poland was responsible for 17.5% of all CO_2 emissions from heat and electricity production within the European Union (including the United Kingdom and Iceland) (European Environment Agency, 2021). In spite of this, the results indicate that Polish cities have some of the lowest CCFs, which stresses the importance of factoring in the level of affluence of the population in the CCF estimation. Polish cities are indeed in the low end in terms of GDP per capita in Europe, and, as described in Section 3.1, the population is likely limited in terms of ability to consume goods and commodities that embed GHG emissions, thus limiting the overall per-capita GHG emissions. With regard to France, the French cities with low CCFs are smaller in terms of area, but densely populated, which could suggest better access to public transport and higher feasibility of transportation modes such as biking or walking. Finally, 71% of electricity in France is produced with nuclear power (IEA, 2021) which results in markedly lower direct emissions from electricity consumption compared to fossil fuel-based electricity production (Lenzen, 2008).

Only one city (out of the 707 cities) has its entire 95% confidence interval below the 1.5 °C boundary in 2020, namely Barranquilla in Colombia. The low per capita CCF estimated for Barranquilla may be due to a high population density, and as described in Section 3.2, for cities in Latin America, private vehicle use accounts for 10% of their consumption-based impacts, and a higher population density may therefore influence car dependency. Finally, the cities of Colombia have the lowest GDP and GDP per capita of all the cities investigated, i.e. their ability to consume and hence pollute is lower than the rest of the cities. Only six cities out of the 707 cities thus have the lower limit of their confidence interval below the 1.5 °C in 2030; found in Colombia, Kenya and Dakar.

Although Colombian cities have some of the lowest CCFs per capita, Colombia have one of the lowest human development index (adjusted for inequalities, 0.59) of the countries assessed. Although still considered a country with high human development, Colombia is struggling with social challenges, such as inequalities in income and education (UNDP, 2022). Considering cities that both have a mean predicted CCF per capita lower than the 1.5 °C target for 2020 and are located in a country classified as having a very high human development index (HDI >0.8; UNDP, 2020), only Granada and Santander in Spain and Brest, Le Mans, Montpellier and Nancy in France fulfills both criteria.

As visible from Fig. 5, none of the Australian cities has CCFs per capita within any of the boundaries neither in 2020 nor in 2030. With an average per capita CCF of 20.4 t CO_2-eq/capita/yr, they need to reduce with a factor 2.9 to fit within the 2.0 °C target for 2020. Before 2030, they need to achieve a reduction of averagely 3.8 to fit within the 2 °C target and to reach the 1.5 °C target they need to reduce with a factor 6.2. Cities in the United States are facing similar challenges with an average per capita CCF of 11.1 t CO_2-eq/capita/yr. To adhere with the 2.0 °C target by 2020 they need to cut their CCF by more than half.

Considering the results presented in Section 3.3 and 3.4 in the perspective of the IPCC guideline, Fig. 5 illustrates that evaluating impacts of cities in a relative perspective, i.e. comparing individual city performance to other cities is not sufficient. Relying on relative targets, e.g. reducing emissions by a certain amount does not ensure compliance with absolute sustainable pathways. Decision-makers therefore need to go beyond this and assess whether the CCF of a city is sufficiently low to adhere with global commitments to climate change mitigation. The mitigation pathways outlined by the IPCC can be scaled to provide absolute targets for cities. Urban policy makers can then use these targets to plan their CCF reduction to sustainable levels in absolute sense, and develop strategies and roadmaps for sustainable urban development.

As mentioned in Section 3.3, it is expected that cities in Africa and other regions of Asia and South America that are largely underrepresented in the 707 cities considered in this work, have similarly low or even lower CCF per capita and would therefore be within the 1.5 °C target in 2030. The impression given by Fig. 5, namely that the majority of cities exceed the boundaries outlined by the IPCC should therefore be interpreted in light of this bias in the dataset and with regard to which world regions are well represented. Cities in Europe, North America (excluding Mexico), East Asia and Oceania, which are well covered regions in the dataset, are indeed expected to be in the high range in terms of per capita CCF. It is likely that with a better coverage of cities in Africa, Asia and South America more cities would perform within the 1.5 °C and 2 °C boundaries. The results presented in Fig. 5 demonstrate that the majority of the cities assessed need to take action to sufficiently reduce their CCF before 2030. Possible actions could be to increase access to public transport and energy-efficient housing. To mitigate emissions embodied in consumption, one possible solution is to impose a carbon tax on imported products to ensure that emissions occurring outside city boundaries are accounted for as well. This is currently being rolled out at EU level as part of the European Green Deal (European Commission, 2021).

4. Conclusion and recommendations

The approach developed in this study shows that cities' CCFs can be estimated using simple MLR models with few, accessible variables. The regression models were trained based on bottom-up studies covering thirteen countries from five continents, ensuring wide applicability for cities across the world. Through the application of the derived models, results showed that out of the 707 assessed cities, Colombian, Kenyan and Senegalese cities currently have the lowest CCFs per capita. It is however important to address the social dimension of sustainability, e.g. by considering the progress of human development, and ensuring that low CCF is not just a product of lower standards of living. Few European cities show promising outlooks both in terms of CCFs that comply with the pathways outlined by the IPCC limiting global warming to 1.5 °C above pre-industrial levels and maintaining a high HDI. Examples include Granada in Spain and Montpellier in France. The models also indicate that of the cities considered, Australian cities are the furthest away from the IPCC's mitigation pathways. Before 2030, Australian cities need to reduce their per capita CCF by more than a factor of 5 to comply with the 1.5 °C pathway. To comply with the 2 °C pathway they still need to reduce by a factor of 3.5.

The simplicity of the proposed regression models supports local decision-makers in keeping track of their emissions and allows them to evaluate the distance to absolute targets such as the IPCC pathways. These models allow the inclusion of emissions embodied in consumption and allow a temporally and spatially dynamic assessment while relying only on globally and consistently available data. As a screening tool, they can be used to identify cities that represent regional climate change hot spots. To mitigate consumption-based climate change impacts associated with the hastily growing urban population, we are however still lacking a method that encompasses the benefits of the method presented in this work while allowing tracing of the main impact contributors. With current methods, we can apply bottom-up assessments such as MFA-LCA at the city level, or build nested city level MRIO models, both of which are labor and data-intensive. Understanding impact contributors and testing the influence of mitigation actions in scenarios is however essential to focus our efforts where it matters. Until such a method exists, applying regression models as described in this work is a way of screening for possible regional impact hotspots to support targeted investigations with e.g. MFA-LCA or MRIO thus saving valuable time and resources.

For now, the models are more consistent with certain world regions, including North America, Europe, and East Asia. Only very few bottom-up studies are available for cities outside these regions especially Africa, South America, and the rest of Asia lacking detailed studies. It is essential that more knowledge is collected on the environmental impact of cities in these regions, as their growth of urban areas will be dramatic in the coming decades. Currently, it is cities in North America, Europe, and East Asia that are responsible for the majority of global emissions of greenhouse gases, and the screening tool presented in this work is, for now, ideal for local governments in these regions. Further research should, however, explore extending the applicability of the screening tool to prepare for the urban growth expected in developing regions. Strengthening the data available in these regions would allow the screening tool to reach global coverage.

CRediT authorship contribution statement

Pernille K. Ohms: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Alexis Laurent:** Conceptualization, Writing – review & editing, Supervision. **Michael Z. Hauschild:** Conceptualization, Writing – review & editing, Supervision. **Morten W. Ryberg:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All supplementary data and results are available in Appendix A, Supplementary Data.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2022.134197.

References

Alfonso Piña, W.H., Pardo Martínez, C.I., 2014. Urban material flow analysis: an approach for Bogotá, Colombia. Ecol. Indicat. 42, 32–42. https://doi.org/10.1016/j.ecolind.2013.10.035.

Arioli, M.S., D'Agosto, M. de A., Amaral, F.G., Cybis, H.B.B., 2020. The evolution of city-scale GHG emissions inventory methods: a systematic review. Environ. Impact Assess. Rev. 80, 106316 https://doi.org/10.1016/j.eiar.2019.106316. November 2019.

Baur, A.H., Förster, M., Kleinschmit, B., 2015a. The spatial dimension of urban greenhouse gas emissions: analyzing the influence of spatial structures and LULC patterns in European cities. Landsc. Ecol. 30 (7), 1195–1205. https://doi.org/10.1007/s10980-015-0169-5.

Baur, A.H., Lauf, S., Förster, M., Kleinschmit, B., 2015b. Estimating greenhouse gas emissions of European cities - modeling emissions with only one spatial and one socioeconomic variable. Sci. Total Environ. 520, 49–58. https://doi.org/10.1016/j.scitotenv.2015.03.030.

Bjorn, A., Chandrakumar, C., Boulay, A.M., Doka, G., Fang, K., Gondran, N., Hauschild, M.Z., Kerkhof, A., King, H., Margni, M., McLaren, S., Mueller, C., Owsianiak, M., Peters, G., Roos, S., Sala, S., Sandin, G., Sim, S., Vargas-Gonzalez, M., Ryberg, M., 2020. Review of life-cycle based methods for absolute environmental sustainability assessment and their applications. Environ. Res. Lett. 15 (8), 083001 https://doi.org/10.1088/1748-9326/AB89D7.

Brauers, H., Oei, P.Y., 2020. The political economy of coal in Poland: drivers and barriers for a shift away from fossil fuels. Energy Pol. 144, 111621 https://doi.org/10.1016/J.ENPOL.2020.111621.

Brown, M.A., Southworth, F., Sarzynski, A., 2008. Shrinking the Carbon Footprint of Metropolitan america. Brookings Report. May, 67.

C40, 2018. Consumption-based GHG Emissions of C40 Cities. March, 17. https://c40-production-images.s3.amazonaws.com/researches/images/68_C40_CBE_Report_FINAL.original.pdf?1520350162.

C40 Cities, 2016. How cities will get the job done. In: C40. https://www.c40.org/researches/deadline-2020.

C40 Cities, 2020. Climate Action Planning Framework, pp. 1–36. https://www.c40.org/researches/unlocking-climate-action-in-megacities.

Clarivate, 2020. Web of Science. https://clarivate.com/webofsciencegroup/.

David, S., 2004. Stern(2004)_Environmental kuznets Curve.pdf. Encycloped. Energy 2, 1–3.

Dias, A.C., Lemos, D., Gabarrell, X., Arroja, L., 2014. Environmentally extended inputeoutput analysis on a city scale e application to Aveiro (Portugal). https://doi.org/10.1016/j.jclepro.2014.04.012.

Erickson, P., Morgenstern, T., 2016. Fixing greenhouse gas accounting at the city scale. Carbon Manag. 7 (5–6), 313–316. https://doi.org/10.1080/17583004.2016.1238743.

European Commission, 2021. Proposal for a Regulation of the European Parliament and of the Council Establishing a Carbon Border Adjustment Mechanism.

European Environment Agency, 2021. Annual European Union Greenhouse Gas Inventory 1990-2019 and Inventory Report 2021. May.

García-Guaita, F., González-García, S., Villanueva-Rey, P., Moreira, T., Feijoo, G., 2018. Integrating urban metabolism, material flow analysis and life cycle assessment in the environmental evaluation of santiago de Compostela. Sustain. Cities Soc. 40, 569–580. https://doi.org/10.1016/j.scs.2018.04.027.

Glaeser, E.L., Kahn, M.E., 2010. The greenness of cities: carbon dioxide emissions and urban development. J. Urban Econ. 67 (3), 404–418. https://doi.org/10.1016/j.jue.2009.11.006.

Gonzalez-Gorman, S., Kwon, S.W., Patterson, D., 2019. Municipal efforts to reduce greenhouse gas emissions: evidence from U.S. cities on the U.S.-Mexico border. Sustainability 11 (17). https://doi.org/10.3390/su11174763.

González-García, S., Dias, A.C., 2019. Integrating lifecycle assessment and urban metabolism at city level: comparison between Spanish cities. J. Ind. Ecol. 23 (5), 1062–1076. https://doi.org/10.1111/jiec.12844.

Hertwich, E.G., Peters, G.P., 2009. Carbon footprint of Nations: a global, trade-linked analysis. Environ. Sci. Technol. 43 (16), 6414–6420. https://doi.org/10.1021/es803496a.

IEA, 2021. France 2021 - Energy Policy Review. Iea. https://iea.blob.core.windows.net/assets/7b3b4b9d-6db3-4dcf-a0a5-a9993d7dd1d6/France2021.pdf.

Ivanova, D., Vita, G., Steen-Olsen, K., Stadler, K., Melo, P.C., Wood, R., Hertwich, E.G., 2017. Mapping the carbon footprint of EU regions. Environ. Res. Lett. 12 (5) https://doi.org/10.1088/1748-9326/aa6da9.

Kalmykova, Y., Rosado, L., Patrício, J., 2016. Resource consumption drivers and pathways to reduction: economy, policy and lifestyle impact on material flows at the national and urban scale. J. Clean. Prod. 132, 70–80. https://doi.org/10.1016/j.jclepro.2015.02.027.

Kanemoto, K., Moran, D., Hertwich, E.G., 2016. Mapping the Carbon Footprint of Nations. https://doi.org/10.1021/acs.est.6b03227.

Kennedy, C.A., Stewart, I., Facchini, A., Cersosimo, I., Mele, R., Chen, B., Uda, M., Kansal, A., Chiu, A., Kim, K.G., Dubeux, C., La Rovere, E.L., Cunha, B., Pincetl, S., Keirstead, J., Barles, S., Pusaka, S., Gunawan, J., Adegbile, M., et al., 2015. Energy and material flows of megacities. Proc. Natl. Acad. Sci. U. S. A 112 (19), 5985–5990. https://doi.org/10.1073/pnas.1504315112.

Kennedy, C., Cuddihy, J., Engel-Yan, J., 2007. The changing metabolism of cities. J. Ind. Ecol. 11 (2), 43–59. https://doi.org/10.1162/jie.2007.1107.

Lavers Westin, A., Kalmykova, Y., Rosado, L., Oliveira, F., Laurenti, R., Rydberg, T., 2019. Combining material flow analysis with life cycle assessment to identify environmental hotspots of urban consumption. J. Clean. Prod. 226, 526–539. https://doi.org/10.1016/j.jclepro.2019.04.036.

Lenzen, M., 2008. Life cycle energy and greenhouse gas emissions of nuclear energy: a review. Energy Convers. Manag. 49 (8), 2178–2199. https://doi.org/10.1016/j.enconman.2008.01.033.

Lenzen, M., Kanemoto, K., Moran, D., Geschke, A., 2012. Mapping the structure of the world economy. Environ. Sci. Technol. 46 (15), 8374–8381. https://doi.org/10.1021/es300171x.

Lorek, S., Gran, C., Lavorel, C., Tomany, S., Oswald, Y., 2021. Equitable 1.5-Degree Lifestyles - How Socially Fair Policies Can Support the Implementation of the European Green Deal.

Mirabella, N., Allacker, K., 2017. The Environmental Footprint of Cities: Insights in the Steps Forward to a New Methodological Approach. https://doi.org/10.1016/j.proenv.2017.03.143.

Moran, D., Kanemoto, K., Jiborn, M., Wood, R., Többen, J., Seto, K.C., 2018. Carbon footprints of 13 000 cities. Environ. Res. Lett. 13 (6) https://doi.org/10.1088/1748-9326/aac72a.

Muñiz, I., Dominguez, A., 2020. The impact of urban form and spatial structure on per capita carbon footprint in u.S. larger metropolitan areas. Sustainability 12 (1), 1–19. https://doi.org/10.3390/su12010389.

Nagendra, H., Bai, X., Brondizio, E.S., Lwasa, S., 2018. The urban south and the predicament of global sustainability. Nat. Sustain. 1 (7), 341–349. https://doi.org/10.1038/s41893-018-0101-5.

Osborne, J.W., 2000. Prediction in multiple regression. Practical Assess. Res. Eval. 7 (2) https://doi.org/10.7275/7j20-gg86.

Revi, A., Satterthwaite, D.E., Aragón-Durand, F., Corfee-Morlot Usa, J., Kiunsi, R.B., da Silva, J., Dodman, D., Maskrey, A., Pahwa Gajjar, S., Balbus, J., Cardona, O.-D., Sverdlik, A., Barros, V., Dokken, D., Mach, K., Bilir, T., Chatterjee, M., Ebi, K., Estrada, Y., et al., 2014. Urban areas. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. William Solecki, pp. 535–612.

Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Séférian, R., Vilariño, M.V., 2018. Mitigation pathways compatible with 1.5°C in the context of sustainable development. In: Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathw. IPCC Special Report Global Warming of 1.5 °C, p. 82. https://www.ipcc.ch/site/assets/uploads/sites/2/2019/02/SR15_Chapter2_Low_Res.pdf.

Rosado, L., Niza, S., Ferrão, P., 2014. A material flow accounting case study of the lisbon metropolitan area using the urban metabolism analyst model. J. Ind. Ecol. 18 (1), 84–101. https://doi.org/10.1111/jiec.12083.

Ryberg, M.W., Andersen, M.M., Owsianiak, M., Hauschild, M.Z., 2020. Downscaling the planetary boundaries in absolute environmental sustainability assessments – a review. J. Clean. Prod. 276, 123287 https://doi.org/10.1016/J.JCLEPRO.2020.123287.

Singh, S., Kennedy, C., 2015. Estimating future energy use and CO2 emissions of the world's cities. Environ. Pollut. 203, 271–278. https://doi.org/10.1016/j.envpol.2015.03.039.

Tian, X., Chang, M., Lin, C., Tanikawa, H., 2014. China's carbon footprint: a regional perspective on the effect of transitions in consumption and production patterns. Appl. Energy 123, 19–28. https://doi.org/10.1016/j.apenergy.2014.02.016.

UNDP, 2022. Human Development Report 2021-22: Uncertain Times, Unsettled Lives: Shaping our Future in a Transforming World. United Nations Development Programme, p. 282.

UN-Habitat, 2020. World cities report 2020. Unpack. Value Sustain. Urban. https://doi.org/10.18356/c41ab67e-en.

UN, 2022. World Economic Situation and Prospects 2022.

UNDP, 2020. The next frontier: human development and the anthropocene. In: Human Development Report 2020.

UNDP, 2021. Peoples' Climate Vote. 1, pp. 1–68. file:///C:/Users/HP/Downloads/Oxford com_compressed (1.pdf.

United Nations, 2019. World Population Prospects 2019. https://population.un.org/wpp/Download/Standard/Population/.

Verma, S., Kandpal, D., 2021. Chapter 16 - green economy and sustainable development: a macroeconomic perspective. In: Environmental Sustainability and Economy. Elsevier Inc. https://doi.org/10.1016/B978-0-12-822188-4.00016-6.

Wang, H., Wang, Y., Wang, H., Liu, M., Zhang, Y., Zhang, R., Yang, J., Bi, J., 2014. Mitigating greenhouse gas emissions from China's cities: case study of Suzhou. Energy Pol. 68, 482–489. https://doi.org/10.1016/j.enpol.2013.12.066.

Watts, M., 2017. Commentary: cities spearhead climate action. Nat. Clim. Change 7 (8), 537–538. https://doi.org/10.1038/nclimate3358.

Wiedmann, T., Chen, G., Owen, A., Lenzen, M., Doust, M., Barrett, J., Steele, K., 2021. Three-scope carbon emission inventories of global cities. J. Ind. Ecol. 25 (3), 735–750. https://doi.org/10.1111/jiec.13063.

Xu, Y., Goodacre, R., 2018. On splitting training and validation set: a comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. J. Anal. Test. 2 (3), 249–262. https://doi.org/10.1007/s41664-018-0068-2.

Yuan, Y., Wang, M., Zhu, Y., Huang, X., Xiong, X., 2020. Urbanization's effects on the urban-rural income gap in China: a meta-regression analysis. Land Use Pol. 99 (August), 104995 https://doi.org/10.1016/j.landusepol.2020.104995.

Zheng, H., Többen, J., Dietzenbacher, E., Moran, D., Meng, J., Wang, D., Guan, D., 2021. Entropy-based Chinese city-level MRIO table framework. Econ. Syst. Res. 1–26. https://doi.org/10.1080/09535314.2021.1932764.