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Carbon footprints of 13,000 cities

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While it is understood that cities generate the majority of carbon emissions, for most cities, towns, and rural areas around the world no carbon footprint (CF) has been estimated. The Gridded Global Model of City Footprints (GGMCF) presented here downscales national CFs into a 250m gridded model using data on population, purchasing power, and existing subnational CF studies from the US, China, EU, and Japan. Studies have shown that CFs are highly concentrated by income, with the top decile of earners driving 30-45% of emissions. Even allowing for significant modeling uncertainties, we find that emissions are similarly concentrated in a small number of cities. The highest emitting 100 urban areas (defined as contiguous population clusters) account for 18% of the global carbon footprint. While many of the cities with the highest footprints are in countries with high carbon footprints, nearly one quarter of the top cities (41 of the top 200) are in countries with relatively low emissions. In these cities population and affluence combine to drive footprints at a scale similar to those of cities in high-income countries. We conclude that concerted action by a limited number of local governments can have a disproportionate impact on global emissions.

Introduction

The IPCC 5th Assessment Report concluded that urban areas generate the majority of carbon emissions from final energy use (Creutzig *et al* 2015, IPCC 2014). However, it is not well understood how carbon footprints are distributed among cities, or how the contribution of total national carbon footprints vary by different types of urban settlements. Detailed carbon footprint (CF) inventories based on local data have been built for a number of individual cities and states (we survey these below). However while reporting standards are emerging (e.g. (Carbon Disclosure Project 2016)) for conducting such assessments, individual city inventories are generally neither comparable nor comprehensive (as discussed in (Fong *et al* 2016, Kennedy *et al* 2010, Pichler *et al* 2017). Furthermore, for most cities no carbon footprint estimate exists.

Urban areas are home to about 54% of total global population and account for more than 70% of global energy use (IPCC 2014, UN Department of Economic and Social Affairs Population Division 2015). Among all cities, economic growth is relatively highly concentrated: it has been estimated that 600 urban centers generate about 60% of global GDP (McKinsey Global Institute 2011). Economists point to this enormous concentration of buying power as an opportunity to develop economic growth strategies focused on a few local governments. If emissions footprints are similarly highly concentrated, then a relatively small number of local governments could have a disproportionate effect on reducing national, and thus global, emissions.

In order to examine the spatial distribution of carbon footprints at the household level, we developed a top-down, globally consistent gridded model. The model uses gridded population and income data to disaggregate existing subnational carbon footprint models for the US, China, Europe, the UK, and Japan, and national data for other countries. While this top-down approach does not take city specific characteristics, such as urban form, subnational variation in carbon intensity of electricity, or building infrastructure into account (variation in these factors is part of the uncertainty ranges accompanying the model results), it does offer some advantages over more detailed bottom-up assessments. First, a top-down method is comprehensive, and can provide results for every city in every country. Second, it has the advantage of consistency. Bottom-up inventories often use different methods, different study boundaries, and are based on different kinds of data, depending on local data availability (Lombardi *et al* 2017), and thus cannot be directly compared. A top-down approach can provide a consistent estimate across many cities.

Methods

Here we present an overview of the Gridded Global Model of Carbon Footprints (GGMCF) model. Additional details can be found in the Supplementary Information. The model uses urban vs. rural consumption patterns and purchasing power as the main predictors of per capita footprint. Income is a strong predictor of CF (Wiedenhofer *et al* 2018). Minx and colleagues (Minx *et al* 2013) found that in the UK the CF of cities is mainly determined by socio-economic rather than geographic and infrastructural drivers, and that income is one of the main determinants. Non-income factors such as car ownership, household size, and education also influence the distribution of footprints. Other studies have reported that income is a useful predictor of an individual's CF, explaining at least 50% of the variation in footprint (Ivanova *et al* 2015, Steen-Olsen *et al* 2016, Weisz and Steinberger 2010), and furthermore even at high levels of income there is no clear evidence that household CF levels off (Isaksen and Narbel 2017, del P. Pablo-Romero and Sánchez-Braza 2016).

Data sources used in each step of the model

1. National carbon footprints, from the Eora global MRIO (Kanemoto *et al* 2016, Lenzen *et al* 2012), for year 2015
2. Existing subnational carbon footprints for USA (31,000 zip codes; Jones and Kammen 2014); China (30 provinces; (Wang *et al* 2015)), Europe (178 NUTS2 regions over 20 countries; (Ivanova *et al* 2017)), UK (408 districts; (Minx *et al* 2013)), and Japan (47 prefectures; (Hasegawa *et al* 2015)).
3. National statistics on the composition of urban vs rural household spending patterns, from Eurostat, US BEA, and the World Bank, covering 113 countries (responsible for 81% of global CO_2 emissions) for year 2015
4. The GHS-POP 250m global gridded population model (Pesaresi and Freire 2016), for year 2015. The GHS-SMOD urbanization layer identifying urban areas, in year 2015. A global map of per-capita purchasing power for 20,159 regions, based on tax statistics collected by the market intelligence company MB International, for year 2015

Table 1 Overview of data sources used to construct the GGMCF model

The GGMCF was built in four steps. Data sources for each step are identified in Table 1. The steps are:

1. National CFs of consumption (CF_n) for 189 countries covering ≈100% of global CO_2 emissions were taken from the Eora multi-region input-output (MRIO) database for the year 2015.
2. For the EU, UK, USA, Japan, and China, existing subnational CF models were used to disaggregate CF_n into subnational regions CF_r, where the regions r range in size from postcode to province (see Table 1). In steps 3 and 4 these subnational regions are treated the same as countries. We use the term "regions" to mean the collection of disaggregated subnational regions plus countries which are not disaggregated.
3. Within each region the CF_r was disaggregated between urban vs rural residents according to the difference in urban vs rural resident expenditure patterns and the total urban vs rural population. For 76 countries (a mixture of developed and developing countries, driving 19% of global CO2 emissions; full list in SI) no comparative expenditure data were available. In these countries all households were assumed to have a national average expenditure pattern.
4. CFs of grid cells within a region were calculated by further disaggregating step 3 using gridded population maps and gridded income data (see Table 1). The first step involved identifying the urban and rural grid cells and subsequently distributing the total urban and rural footprint on the basis of the share of aggregate purchasing power in each cell. Urban cells were identified using the GHS-SMOD layer of urban areas (high and low density population clusters). GHS-SMOD uses a clustering algorithm to identify urban areas as clusters of contiguous cells with a total population and population density above specified thresholds. Aggregate purchasing power per grid cell was determined by multiplying the population in the cell by the mean purchasing power at that location. Carbon footprints of cities are then defined as the CF of those cells in the GHS-SMOD layer that are high-density clusters of contiguous grid cells with ≥1500 inhabitants/km^2 and with a minimum population of 50,000 (see below).

Defining “cities” is not trivial (Uchiyama and Mori 2017). In some countries there are up to seven levels of administrative divisions. In this model the EU Global Human Settlement Layer, GHS-SMOD, was used. GHS-SMOD identifies “towns” as low-density clusters of contiguous grid cells with ≥300 inhabitants/km^2 with a minimum population of 5000, and “cities” as high-density clusters of contiguous grid cells with ≥1500 inhabitants/km^2 with a minimum population of 50 000. GHS-SMOD defines 13,844 cities and 96,336 towns. Since GHS-SMOD identifies clusters looking at contiguous urban fabric, this often includes suburbs and exurbs and thus the urban areas identified in GHS-SMOD are generally larger than the strict legal boundaries of a city jurisdiction. This issue particularly affects contiguous urban fabric e.g. Tokyo/Yokohama, New York, New Jersey, Guangzhou/Hong Kong, and similar cases. Using other spatial administrative divisions would be useful in delineating administrative responsibility within contiguous urban fabric. Per-city GDP (gross domestic product; note this is also sometimes called gross regional product when calculated for subnational regions) was calculated by applying the GHS-SMOD city boundaries to the G-Econ 4.0 (Nordhaus 2006) global gridded model of GDP.

The results provided by this top-down model provide a general view of how consumption hotspots drive global emissions and to identify patterns, similarities, and clusters, and can offer a rough comparison of CFs across urban areas. However to more accurately compare the CFs of individual households and cities or to track how a city’s footprint evolves over time, more detailed models and accounts based on local data are needed.

There are a number of assumptions and sources of uncertainty and variability at the household and city level that can affect the results. These sources of uncertainty and variability can be categorized in several broad groups: (1) the relative carbon intensity of equivalent expenditure in urban vs. rural areas is assumed to be equal (i.e. we assume $1 of expenditure in a product category in an urban and rural area are equally carbon intensive). (2) The consumption patterns of urban and rural residents are assumed to be homogenous within each region. This is not so problematic when the region is a postcode as in the case of the US, but is a bigger issue when the region is large, e.g. India. In future development of the GGMCF model we do anticipate including more subnational CF assessments as they become available. (3) As with consumption patterns, purchasing power is homogenous within each of the regions identified by the purchasing power database. (4) Direct emissions from households, which importantly includes heating (or district heating) and vehicle fuel, are currently attributed evenly per capita across each region. (5) The CF associated with non-household national expenditure (primarily government spending and capital formation) is currently allocated evenly per capita in each region. The rationale for this decision was so that the model allocates 100% of total emissions. Note that excluding these emissions from essential services would lead to even more relative inequality among households within a country as the results would then consider only discretionary spending and not common infrastructure (health, education, highways, etc.). In the countries for which subnational models were used we followed their regional allocation of non-household expenditure. (6) Allocation and aggregation error are possible, including in the matching of purchasing patterns to the corresponding goods in the IO model, the inclusion of utilities in rent, and varying carbon intensity of same-sector goods (e.g. electricity may have different carbon intensity in different areas of a country). One study by (Min and Rao 2017) suggests that such errors lead to an uncertainty of ±20% for household footprints. (7) Error in the national CF results from Eora (this has a heteroskedastic distribution among countries, with the error <±10% for most developed countries, up to ±25% for others, and a tail distribution of smaller countries with higher uncertainty (Moran and Wood 2014, Inomata and Owen 2014)).

To account for all of these source of uncertainty the model was subjected to a sensitivity analysis with generous margins of uncertainty. Confidence was estimated for all results by allowing the per-capita CF estimates at the grid cell and individual city level to vary with a coefficient of variation of 1.0 to 10.0 (i.e. meaning it is 99% likely that the correct value is within ±300-3000% of the model estimated result). To construct the range of alternative global Lorenz curves (shown as shaded areas in Figs. 3 and 4) a Monte Carlo procedure was employed. The total carbon footprint per grid cell (CF_i) was randomly drawn from a normal distribution using mean μ_i equal to the original CF_i estimate and two different scenarios for variance σ_i^2. In the “lower uncertainty” scenario, σ_i^2 is specified such that the coefficient of variation CV (the standard deviation relative to the mean, or σ_i/μ_i) CV=1.0, and in the “higher uncertainty” scenario $\sigma_i/\mu_i = 10$. During the sampling CF_i was constrained to a lower limit of 1% of the original estimate to prevent negative values. The resulting CFs were then normalized within each region to sum to the total CF_r for that region r, where during each perturbation CF_r was itself also randomly drawn from a normal distribution with CV=0.25 in order to account for both the uncertainty of the national CF result from the Eora database and the uncertainty of the subnational disaggregation where that was used. A Lorenz curve was constructed for each perturbation scenario, and the shaded ranges in Fig. 3 indicates the range of these alternative Lorenz curves in the two scenarios. The variance of individual city CFs were calculated in a similar manner. All urban cells within a country were assumed to have a CV=10.0, and the total rural footprint in a country assumed to have a CV=1.0. This allows for uncertainty around the splitting of footprint into urban and rural components. These sampled values were then rescaled to sum to CF_r, which again was itself sampled from a normal distribution with CV=0.25. The CF of each city was calculated during each perturbation, and the variance of each city CF was taken from the population of perturbed results.

Results & Discussion

The gridded model results are shown in absolute value in Fig. 1 and in per capita terms in Fig. 2.

Fig. 1 Gridded model of carbon footprints. High-income cities in Europe and US and dense middle- and upper-income cities in Asia are emissions hotspots in absolute terms.

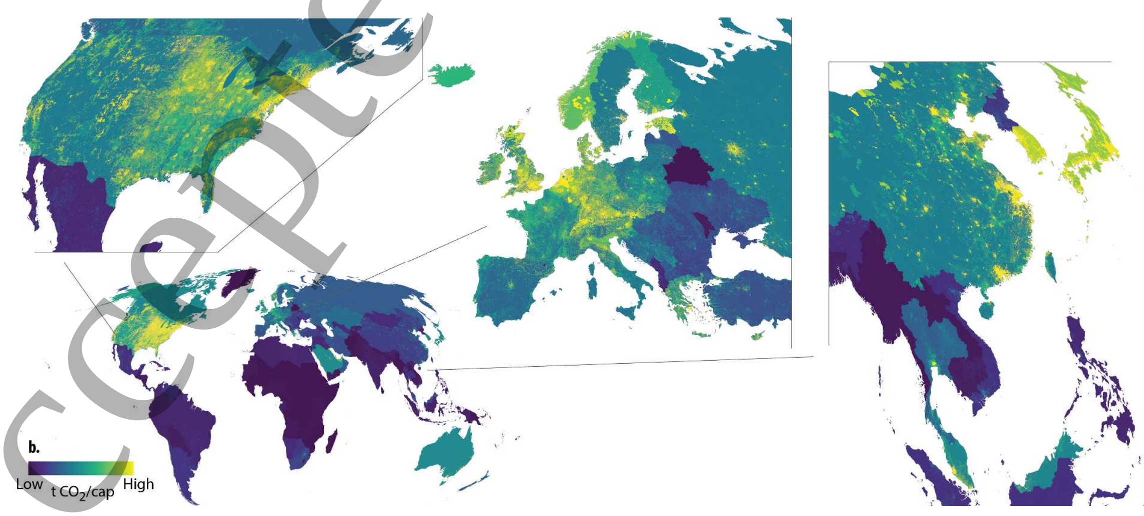

Fig. 2 Per capita results from gridded model of carbon footprints. Per capita CFs are also spatially concentrated. High per capita CFs are typically coincident with dense areas. Zoom-in panels are color-scaled independently.

Similar to the concentration of economic activity, we find that a relatively few number of urban areas account for a disproportionate share of the world's carbon footprint (Fig. 3). The top 100 urban areas by carbon footprint contain 11% of the world's population but drive 18% of the global CF. In most countries a few urban areas account for a disproportionate share of the total footprint. In 98 of the 187 countries assessed, the top three urban areas drive more than one-quarter of the national CF. City footprints generally correspond to their share of the population. This degree of concentration within countries indicates that in many cases local-level governments have jurisdiction over emissions of the same order of magnitude as national governments.

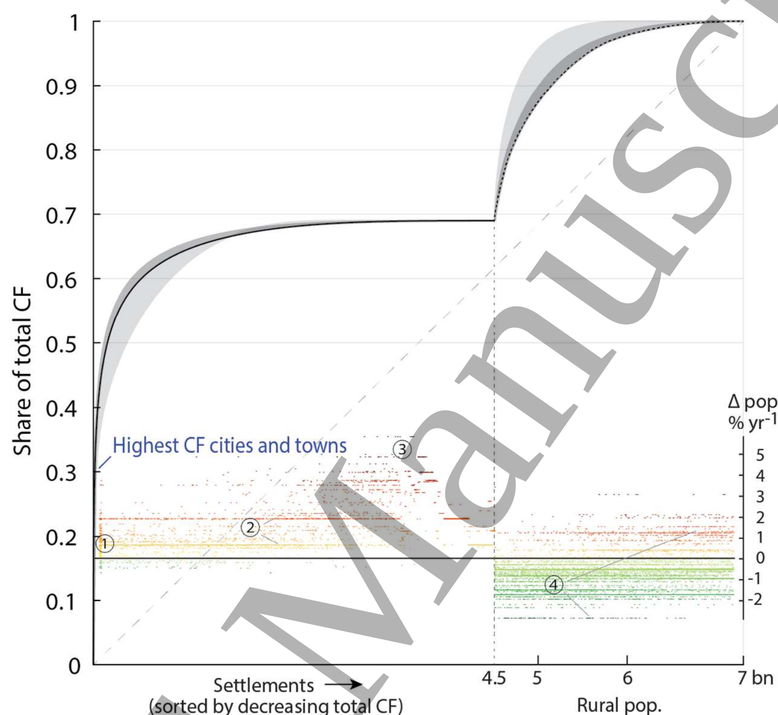

Fig. 3 Urban areas contain 60% of global population and drive ~68% of global CF. But within this the CF is highly concentrated in a small number of high CF urban areas and high CF per-capita exurbs, while populous low CF urban rural areas contribute relatively little to the total global CF. Shaded area shows the range of alternative Lorenz curves constructed during the sensitivity analysis, with coefficient of variation = 1.0 (dark shading) and 10.0 (lighter shading) (see SI for details). Comparing city CF to projected growth rate (lower graph; same x-axis but independent y axis) reveals highest growth in low CF urban areas (zone ③) and declining growth in rural areas (zone ④). Other notable features include ① modestly high growth rates, around 1-2% yr^{-1} for top-CF urban areas, ② horizontal bands visible for urban clusters in India (1.9% projected growth rate) and China (0.6% projected growth rate) across all city sizes, ③ the fastest-growing urban areas currently contribute little to global CF, and ④ declining rural populations all CF $pers.^{-1}$, with rural depopulation in Japan (-2.8% pers. yr^{-1}1) visible, but some projected growth in the least CF-intensive regions. The Lorenz curve is computed for individual urban clusters each of which consist of varying numbers of grid cells.

Plotting a Lorenz curve (showing cumulative population in descending order of intensity vs. the cumulative carbon footprint) reveals the degree of concentration, i.e. how much of the total global carbon footprint are the top N% of emitters responsible for. Our results corroborate previous studies showing that CFs are highly concentrated. Hubacek and colleagues (Hubacek *et al* 2017) estimated that the top 10% of income-earners globally drive 30% of global GHG emissions; Chancel and Pikkety (Chancel and Pikkety 2015) estimated the top decile to drive 45%, and our results (Fig. 4) indicate that the top decile drive between 38% and 47%-68% (lower and higher uncertainty estimates) of global emissions.

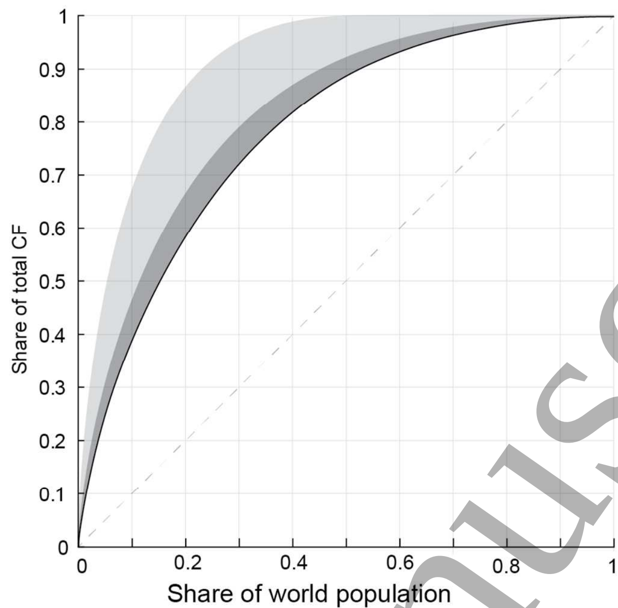

Fig 4. The Lorenz curve of gridded carbon footprints shows highest CF per-capita decile of population drives ~35% of the global carbon footprint. The shaded area indicate the range of alternative Lorenz curves constructed during the sensitivity analysis (dark indicates coefficient of variation=1.0; lighter indicates coefficient of variation=10.0; see SI for details). Most of the scenarios from the uncertainty analysis suggest a more unequal distribution of carbon footprints than the base model predicts. This is because CFs must be greater than zero and, at the same time, can be become many times larger as those from the base model and thus the scenarios in the sensitivity analysis are constrained with a lower bound of 10% of the original CF but no upper bound. Note: this Lorenz curve is computed at grid cell level, but error measurements for individual cities were calculated separately and used in Figs. 3 and 5.

It is possible to use the model to identify top CF urban areas globally (Fig. 5; full list of top urban areas is provided at the website and in the SI) and to decompose the role of population size and carbon intensity (CF per capita) in the total CF.

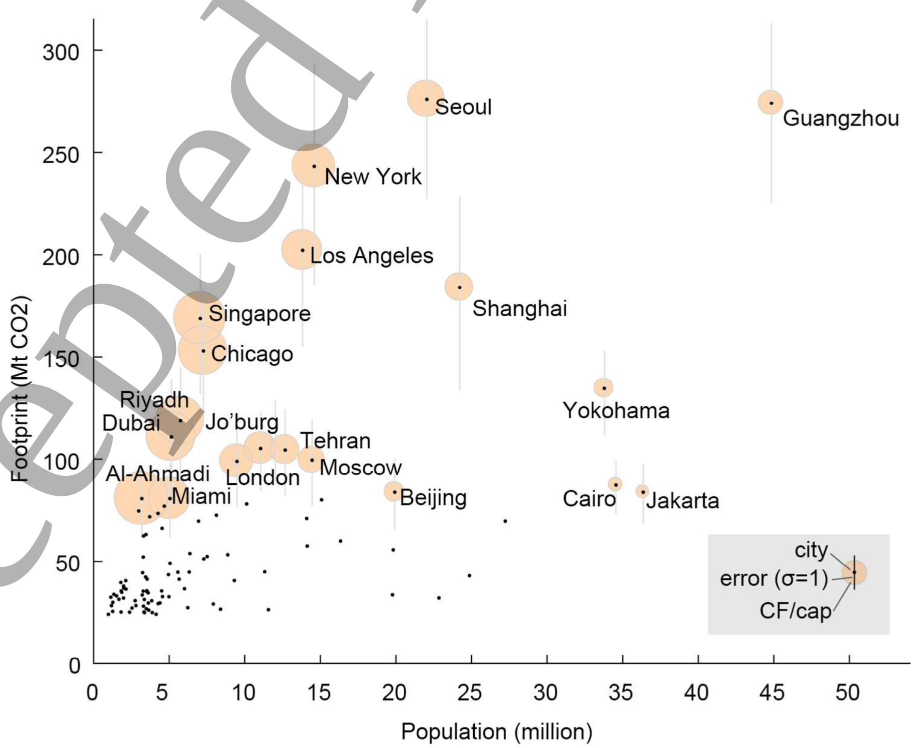

Fig 5. The urban clusters with the largest total footprints (named here are the top 20) have a large CF due to a combination of population and high CF per capita (bubble size). Cairo and Jakarta have relatively low CF per capita but large populations, while Miami and Al-Ahmadi in Kuwait have smaller populations with higher average footprints, and thus similar total CFs. Vertical lines show one standard deviation for each city CF estimate.

While many of the urban areas with the highest CF are in countries with high carbon footprints, 41 of the top 200 (e.g. Dhaka, Cairo, Lima) are in countries where total and per capita emissions are low (e.g. Senegal, Egypt, Peru). In these urban areas, population and affluence combine to drive footprints at a similar scale as counterparts in the highest income countries.

The largest urban clusters almost all have carbon footprints in excess of their direct emissions (Fig. 6). This means if their carbon accounts do not include indirect emissions embodied in consumption, they will under-estimate their total carbon footprint. Among mid-tier population urban areas, there is a clear differentiation by city GDP: midsize urban areas with a lower GDP are usually net exporters, with direct Scope 1 emissions greater than their Scope 3 footprint, while midsize urban areas with a higher GDP are importers (Fig 6). Smaller urban clusters are predominantly importers. The division between wealthy consumer areas and lower-income producer areas clearly stands out. Urban areas with higher GDP, and small towns, tend to have Scope 3 footprints larger than their direct emissions.

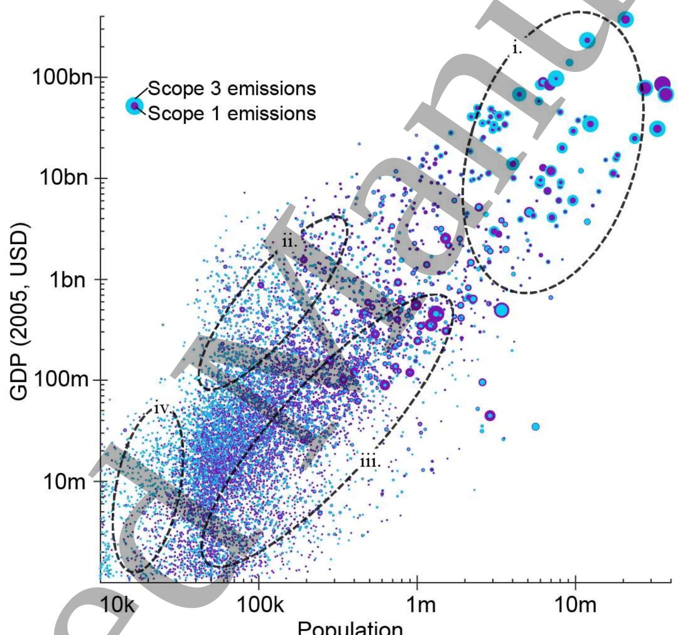

Fig. 6 : Types of urban areas: i. populous, high GDP with large footprints (Scope 3 exceeds Scope1); ii. smaller, mid-GDP net embodied carbon importers (Scope 1>Scope 3); iii. larger, low GDP producers (carbon exporters); and iv. smaller communities where predominantly Scope 3>Scope 1

In addition to the role of key large and/or affluence cities in driving the global CF, the contribution of affluent, low-density areas is also clear. The top 5% of non-urban residents globally (by CF per capita) generate 32% of the entire national footprint in the US, and a similar share (21%) in China. In those two countries, the top ten urban plus top 5% of suburban residents drive more than half of the national carbon footprint. In most countries, however, even the most footprint-intensive suburbs are outshone by the scale of consumption in urban centers.

Given expected urbanization trends (cities are projected to add 2.5-3 billion inhabitants by 2050), it is important to understand whether the most footprint-intensive cities are also the fastest growing. The model results show that current footprint hotspots are not in the fastest-growing cities (Fig. 3). But if left to grow with today's current per-capita footprint intensity, the global carbon footprint will grow and spread. The fastest-growing cities today contribute a minority share to the global footprint, but this can be expected to change as those cities grow in terms of infrastructure, population, and affluence.

While urban direct emissions and associated reduction opportunities are comparatively well-studied (e.g. (Satterthwaite 2008, Hurth and McCarney 2015, Grubler *et al* 2012, Kennedy *et al* 2014) the full emissions driven by households include significant indirect emissions embodied in supply chains e.g. from travel, food, and imported goods. Considering the complete Scope 3 footprint induced by consumption can expand a city's carbon footprint 2-3 times over its direct emissions (Minx *et al* 2013, Feng *et al* 2014, Athanassiadis *et al* 2016, Wackernagel *et al* 2006, Lin *et al* 2015, Fry *et al* 2017). State and local governments can benefit by better understanding the distribution and drivers of footprints. While national-level policies can be powerful, programs can be more effective if they are targeted to consider local consumer profiles, including income and consumption patterns which vary across regions (Jones and Kammen 2011, Minx *et al* 2013, Baiocchi *et al* 2010, Chen *et al* 2018).

Cities can consider options to lower their induced footprint beyond their direct Scope 1 emissions (Creutzig *et al* 2016, Croci *et al* 2017, Chen *et al* 2017). Local governments can encourage low-carbon lifestyles through traditional direct tools such as taxation and regulation, using soft policies to encourage businesses and households to reduce their carbon footprints, adopting green purchasing practices, and advancing demand-side management measures e.g. to reduce energy waste, encourage lower-carbon diets, and decelerate demand for discretionary air travel. Cities may also adopt more radical de-carbonization policies, such as restricting private cars in the city center, aggressively rewarding vehicle electrification, and take advantage of the fact that many of the highest-income, highest-consumption households may be willing and able to pay for decarbonization, for example by shifting the entire city electricity supply to renewables. In comparison to national or state-level policies, cities can more easily direct programs to target different districts and demographic segments. Experimentation, iteration, and sharing success stories will be key to this process (Castán Broto and Bulkeley 2013).

There have been many studies to calculate CFs for individual cities. Most of such studies consider multiple cities; this is advantageous both because it benefits multiple cities and also because single studies generally use the same method and system boundaries so within one study city CFs can be compared. (Kennedy *et al* 2009) and (Sovacool and Brown 2010) provided some of the first such studies, calculating footprints of 10 and 12 megacities respectively. The C40 coalition of cities used an MRIO-based method to estimate the footprint of 79 cities ((C40 Cities 2018). Other studies covering in the range of 2-10 cities include (Creutzig *et al* 2015, Hu *et al* 2016, Lin *et al* 2015, Isman *et al* 2017, Feng *et al* 2014, Baabou *et al* 2017, Fry *et al* 2017, Kennedy *et al* 2015). The city footprint databases initiated by the Carbon Disclosure Project and the website http://metabolismofcities.com are beginning to collect individual city CF results. Collecting such results should help improve and refine CF results for individual cities. Establishing frameworks for city footprints has been discussed by (Lenzen and Peters 2009, Dodman 2009). A recent innovation has been combining a foreground city or regional input-output table with a larger background global MRIO table (Wiedmann *et al* 2015).

GHG mitigation efforts become easier to realize when specific leverage points can be identified. Recent studies have shown that emissions are concentrated not only spatially but in other dimensions as well. For example in China a small number of industries and provinces account for the bulk of emissions embodied in exports (Liu *et al* 2015). Other recent work on spatially explicit footprints has been able to locate emissions hotspots driven by a given set of consumers (Kanemoto *et al* 2016). Continued research to pinpoint hotspots of consumption and emissions and to isolate carbon intensive nodes in global supply chains will make it easier to take specific and practical measures to reduce carbon intensity at those leverage points.

Conclusion

Cities represent intense concentrations of populations and consumption. Even allowing considerable margins of uncertainty it is clear that footprints are highly concentrated. The spatially disaggregated map of carbon footprints presented here can help address a range of further questions regarding strategies to reduce carbon footprint. Beyond identifying hotspots, spatially explicit models of carbon footprints can be used together with scenarios on population dynamics to forecast urban footprints, connected to marketing or demographic data to help target policies (ultimately, conceivably even to the neighborhood or individual level), and compared with other spatial data, for example of expected climate-related impacts. Our results suggest that there is significant opportunity for focusing strategies to reduce CF to a few hundred localities. The confluence of high concentration of global GDP and global CFs augurs well for future development of innovative strategies to reduce footprints. The fact that CFs are highly concentrated in affluent cities means that targeted measures in a few places and by selected coalitions can have a large effect covering important consumption hotspots.

The model results are available at the GGMCF website: http://folk.ntnu.no/daniemor/cities [temporary URL]

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Author contributions
DM conceived and led the work. KK, RW, and JT contributed to the modeling and analysis. MJ and KS contributed to the writing.

Additional Information
None of the authors have any competing financial interests.

Athanassiadis A, Christis M, Bouillard P, Vercalsteren A, Crawford R H and Khan A Z 2016 Comparing a territorial-based and a consumption-based approach to assess the local and global environmental performance of cities *J. Clean. Prod.* Online: http://www.sciencedirect.com/science/article/pii/S095965261631678X

Baiocchi G, Minx J and Hubacek K 2010 The Impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom *J. Ind. Ecol.* **14** 50–72 Online: http://www.scopus.com/inward/record.url?eid=2-s2.0-77954352238&partnerID=40&md5=9160d6903deddf2b0a800014088174d3

Baabou W, Grunewald N, Ouellet-Plamondon C, Gressot M and Galli A 2017 The Ecological Footprint of Mediterranean cities: Awareness creation and policy implications *Environ. Sci. Policy* **69** 94–104

C40 Cities 2018 *Consumption based GHG emissions of C40 cities* Online: http://www.c40.org/researches/consumption-based-emissions

Carbon Disclosure Project 2016 *Global Cities Report 2016*

Castán Broto V and Bulkeley H 2013 A survey of urban climate change experiments in 100 cities *Glob. Environ. Chang.* **23** 92–102

Chancel L and Pikkety T 2015 *Carbon and inequality: from Kyoto to Paris* (Paris) Online: http://piketty.pse.ens.fr/files/ChancelPiketty2015.pdf

Chen G, Hadjikakou M and Wiedmann T 2017 Urban carbon transformations: unravelling spatial and inter-sectoral linkages for key city industries based on multi-region input–output analysis *J. Clean. Prod.*

Chen G, Hadjikakou M, Wiedmann T and Shi L 2018 Global warming impact of suburbanization: The case of Sydney *J. Clean. Prod.* **172** 287–301 Online: http://www.sciencedirect.com/science/article/pii/S095965261732468X

Creutzig F, Baiocchi G, Bierkandt R, Pichler P-P and Seto K C 2015 Global typology of urban energy use and potentials for an urbanization mitigation wedge. *Proc. Natl. Acad. Sci. U. S. A.* **112** 6283–8 Online: http://www.ncbi.nlm.nih.gov/pubmed/25583508

Creutzig F, Agoston P, Minx J C, Canadell J G, Andrew R M, Quere C Le, Peters G P, Sharifi A, Yamagata Y and Dhakal S 2016 Urban infrastructure choices structure climate solutions *Nat. Clim. Chang.* **6** 1054–6 Online: http://dx.doi.org/10.1038/nclimate3169

Croci E, Lucchitta B, Janssens-Maenhout G, Martelli S and Molteni T 2017 Urban CO2 mitigation strategies under the Covenant of Mayors: An assessment of 124 European cities *J. Clean. Prod.* Online: http://www.sciencedirect.com/science/article/pii/S0959652617311174?via%3Dihub

Dodman D 2009 Blaming cities for climate change? An analysis of urban greenhouse gas emissions inventories *Environ. Urban.* **21** 185–201 Online: http://journals.sagepub.com/doi/abs/10.1177/0956247809103016

Feng K, Hubacek K, Sun L and Liu Z 2014 Consumption-based CO2 accounting of China's megacities: The case of Beijing, Tianjin, Shanghai and Chongqing *Ecol. Indic.* **47**

Fong W K, Sotos M, Doust M, Schultz S, Marques A and Deng-Beck C 2016 *Global Protocol for Community-Scale Greenhouse Gas Emission Inventories* Online: http://www.ghgprotocol.org/city-accounting

Fry J, Lenzen M, Jin Y, Wakiyama T, Baynes T, Wang Y, Malik A, Geschke A and Chen G 2017 Assessing carbon and resource footprints of cities *J. Clean. Prod.* Online: https://www.sciencedirect.com/science/article/pii/S0959652617327336

Grubler A, Bai X, Buettner T, Dhakal S, Fisk D J, Ichinose T, Keirstead J E, Sammer G, Satterthwaite D, Schulz N B, Shah N, Steinberger J and Weisz H 2012 Chapter 18 - Urban Energy Systems *Global Energy Assessment - Toward a Sustainable Future* (Cambridge University Press, Cambridge, UK and

New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria) pp 1307–400

Hasegawa R, Kagawa S and Tsukui M 2015 Carbon footprint analysis through constructing a multi-region input–output table: a case study of Japan *J. Econ. Struct.* **4** 5 Online: http://www.journalofeconomicstructures.com/content/4/1/5

Hu Y, Lin J, Cui S and Khanna N Z 2016 Measuring Urban Carbon Footprint from Carbon Flows in the Global Supply Chain *Environ. Sci. Technol.* **50** 6154–63 Online: http://pubs.acs.org/doi/abs/10.1021/acs.est.6b00985

Hubacek K, Baiocchi G, Feng K, Muñoz Castillo R, Sun L and Xue J 2017 Global carbon inequality *Energy, Ecol. Environ.* **2** 361–9 Online: https://doi.org/10.1007/s40974-017-0072-9

Hurth V and McCarney P 2015 International standards for climate-friendly cities *Nat. Clim. Chang.* **5** 1025–6 Online: http://www.nature.com/doifinder/10.1038/nclimate2823

Inomata S and Owen A 2014 Comparative Evaluation Of MRIO Databases *Econ. Syst. Res.* **26** 239–44 Online: http://dx.doi.org/10.1080/09535314.2014.940856

IPCC 2014 *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, Switzerland)

Isaksen E T and Narbel P A 2017 A carbon footprint proportional to expenditure - A case for Norway? *Ecol. Econ.* **131** 152–65

Isman M, Archambault M, Charles N K, Lin D, Iha K and Ouellet-Plamondon C 2017 Ecological Footprint assessment for targeting climate change mitigation in cities: A case study of 15 Canadian cities according to census metropolitan areas (CMA) *J. Clean. Prod.* Online: http://www.sciencedirect.com/science/article/pii/S0959652617324976?utm_content=buffer07b39&utm_medium=social&utm_source=facebook.com&utm_campaign=buffer

Ivanova D, Stadler K, Steen-Olsen K, Wood R, Vita G, Tukker A and Hertwich E G 2015 Environmental Impact Assessment of Household Consumption *J. Ind. Ecol.* **20** 526–36

Ivanova D, Vita G, Steen-Olsen K, Stadler K, Melo P C, Wood R, Hertwich E G, Ivanova D, Vita G, Steen-Olsen K, Melo P C, Stadler K, Wood R and Hertwich E G 2017 Mapping the carbon footprint of EU regions *Environ. Res. Lett.* **12**

Jones C M and Kammen D M 2011 Quantifying carbon footprint reduction opportunities for U.S. households and communities *Environ. Sci. Technol.* **45** 4088–95

Kanemoto K, Moran D D and Hertwich E G 2016 Mapping the Carbon Footprint of Nations *Environ. Sci. Technol.* **50** 10512–10517

Kennedy C, Steinberger J, Gasson B, Hansen Y, Hillman T, Havránek M, Pataki D, Phdungsilp A, Ramaswami A and Mendez G V 2009 Greenhouse Gas Emissions from Global Cities *Environ. Sci. Technol.* **43** 7297–302 Online: http://dx.doi.org/10.1021/es900213p

Kennedy C, Steinberger J, Gasson B, Hansen Y, Hillman T, Havránek M, Pataki D, Phdungsilp A, Ramaswami A and Mendez G V 2010 Methodology for inventorying greenhouse gas emissions from global cities *Energy Policy* **38** 4828–37

Kennedy C A, Ibrahim N and Hoornweg D 2014 Low-carbon infrastructure strategies for cities *Nat. Clim. Chang.* **4** 343–6 Online: http://dx.doi.org/10.1038/nclimate2160

Kennedy C A, Stewart I, Facchini A, Cersosimo I, Mele R, Chen B, Uda M, Kansal A, Chiu A, Kim K-G, Dubeux C, Lebre La Rovere E, Cunha B, Pincetl S, Keirstead J, Barles S, Pusaka S, Gunawan J, Adegbile M, Nazariha M, Hoque S, Marcotullio P J, González Otharán F, Genena T, Ibrahim N, Farooqui R, Cervantes G and Sahin A D 2015 Energy and material flows of megacities. *Proc. Natl. Acad. Sci. U. S. A.* **112** 5985–90 Online: http://www.ncbi.nlm.nih.gov/pubmed/25918371

Lenzen M, Kanemoto K, Moran D and Geschke A 2012 Mapping the structure of the world economy *Environ. Sci. Technol.* **46** 8374–8381

Lenzen M and Peters G M 2009 How City Dwellers Affect Their Resource Hinterland *J. Ind. Ecol.* **14** 73–90 Online: http://doi.wiley.com/10.1111/j.1530-9290.2009.00190.x

Lin J, Hu Y, Cui S, Kang J and Ramaswami A 2015 Tracking urban carbon footprints from production and consumption perspectives *Environ. Res. Lett.* **10** 54001 Online: http://stacks.iop.org/1748-9326/10/i=5/a=054001?key=crossref.cb2b1c3d48ad74cc88ba98fc4f917be8

Liu Z, Davis S J, Feng K, Hubacek K, Liang S, Anadon L D, Chen B, Liu J, Yan J and Guan D 2015 Targeted opportunities to address the climate-trade dilemma in China *Nat. Clim. Chang.* **6** 201–6 Online: http://dx.doi.org/10.1038/nclimate2800

Lombardi M, Laiola E, Tricase C and Rana R 2017 Assessing the urban carbon footprint: An overview *Environ. Impact Assess. Rev.* **66** 43–52 Online: http://www.sciencedirect.com/science/article/pii/S0195925517301245

McKinsey Global Institute 2011 *Urban world: Mapping the economic power of cities*

Min J and Rao N D 2017 Estimating Uncertainty in Household Energy Footprints *J. Ind. Ecol.* Online: http://doi.wiley.com/10.1111/jiec.12670

Minx J, Baiocchi G, Wiedmann T, Barrett J, Creutzig F, Feng K, Förster M, Pichler P-P, Weisz H and Hubacek K 2013 Carbon footprints of cities and other human settlements in the UK *Environ. Res. Lett.* **8** 35039 Online: http://stacks.iop.org/1748-9326/8/i=3/a=035039

Moran D and Wood R 2014 Convergence Between the Eora, WIOD, EXIOBASE, and OpenEU's Consumption-Based Carbon Accounts *Econ. Syst. Res.* **26** 245–61 Online: http://www.tandfonline.com/doi/abs/10.1080/09535314.2014.935298

Nordhaus W D 2006 Geography and macroeconomics: new data and new findings. *Proc. Natl. Acad. Sci. U. S. A.* **103** 3510–7 Online: http://www.ncbi.nlm.nih.gov/pubmed/16473945

del P. Pablo-Romero M and Sánchez-Braza A 2016 The changing of the relationships between carbon footprints and final demand: Panel data evidence for 40 major countries *Energy Econ.*

Pesaresi M and Freire S 2016 *GHS Settlement grid following the REGIO model 2014 in application to GHSL Landsat and CIESIN GPW v4-multitemporal (1975-1990-2000-2015)* Online: http://data.europa.eu/89h/jrc-ghsl-ghs_smod_pop_globe_r2016a

Pichler P-P, Zwickel T, Chavez A, Kretschmer T, Seddon J and Weisz H 2017 Reducing Urban Greenhouse Gas Footprints *Sci. Rep.* **7** 14659 Online: https://doi.org/10.1038/s41598-017-15303-x

Satterthwaite D 2008 Cities' contribution to global warming: notes on the allocation of greenhouse gas emissions *Environ. Urban.* **20** 539–49 Online: http://eau.sagepub.com/cgi/doi/10.1177/0956247808096127

Sovacool B K and Brown M A 2010 Twelve metropolitan carbon footprints: A preliminary comparative global assessment *Energy Policy* **38** 4856–69

Steen-Olsen K, Wood R and Hertwich E G 2016 The Carbon Footprint of Norwegian Household Consumption 1999-2012 *J. Ind. Ecol.* **20** 582–92 Online: http://doi.wiley.com/10.1111/jiec.12405

Uchiyama Y and Mori K 2017 Methods for specifying spatial boundaries of cities in the world: The impacts of delineation methods on city sustainability indices *Sci. Total Environ.* **592** 345–56 Online: http://www.sciencedirect.com/science/article/pii/S0048969717305193

UN Department of Economic and Social Affairs Population Division 2015 *World Urbanization Prospects (2014 Edition)* Online: https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Report.pdf

Wackernagel M, Kitzes J, Moran D, Goldfinger S and Thomas M 2006 The Ecological Footprint of cities and regions: Comparing resource availability with resource demand *Environ. Urban.* **18** 103–12

Wang Y, Geschke A and Lenzen M 2015 Constructing a Time Series of Nested Multiregion Input–Output Tables *Int. Reg. Sci. Rev.*

Weisz H and Steinberger J K 2010 Reducing energy and material flows in cities *Curr. Opin. Environ. Sustain.* **2** 185–92

Wiedenhofer D, Smetschka B, Akenji L, Jalas M and Haberl H 2018 Household time use, carbon footprints, and urban form: a review of the potential contributions of everyday living to the 1.5 °C climate target *Curr. Opin. Environ. Sustain.* **30** 7–17 Online: https://www.sciencedirect.com/science/article/pii/S1877343517301318

Wiedmann T O, Chen G and Barrett J 2015 The Concept of City Carbon Maps: A Case Study of Melbourne, Australia *J. Ind. Ecol.* **20** 676–91 Online: http://doi.wiley.com/10.1111/jiec.12346