Carbon footprints of 13,000 cities

Supplementary Information – Annex

Daniel Moran, Keiichiro Kanemoto, Magnus Jiborn, Richard Wood, Johannes Többen, Karen Seto

This annex contains details about methods and data sources.

Model overview

We started with the national CF of consumption for each country as calculated using the Eora MRIO (Kanemoto et al. 2016; Lenzen et al. 2012). For 24 countries (EU + UK, USA, Japan, and China) existing subnational regional models of CF were available (documented below). For these countries we split the national CF across the regions then proceeded treating each region as a country. We then split the CF of each region between urban and rural residents using the national urban vs. rural expenditure pattern data from the World Bank, Eurostat, and US BEA. We then allocated the national urban footprint to footprints to grid cells within the country by first identifying grid cells as either urban or rural, then apportioning the footprint on the basis of the share of aggregate purchasing power in each cell. Urban cells were those identified as Settlements in the GHS-SMOD model. Aggregate purchasing power per grid cell was determined by multiplying the EU Global Human Settlement Layer (GHS-POP) gridded population model by spatially explicit sub-national purchasing data from censuses and surveys gathered by the marketing intelligence company MB International. The model assumes that $1 of expenditure on a product category in urban vs. rural areas is equally carbon intensive; that direct emissions from households (which importantly includes heating and vehicle fuel) are homogenous nationally; and allocates carbon footprints associated with capital formation evenly per capita nationally. In each grid cell we know only whether it is urban or rural (and the associated purchasing pattern), total expenditure, and total population. These assumptions were made for lack of globally consistent data upon which to make superior choices. These sources of uncertainty are accounted for in the Monte Carlo uncertainty analysis, discussed below.

The model uses urban vs. rural consumption patterns and purchasing power as the main predictors of per capita footprint. Minx and colleagues 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 (Minx et al. 2013). 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 & Steinberger 2010), and furthermore even at high levels of income there is no clear evidence that the personal CF levels off (Isaksen & Narbel 2017; del P. Pablo-Romero & Sánchez-Braza 2016). Bottom-up approaches based on local survey data are more sensitive to variations amongst cities and individuals than top-down approaches can be.

The results presented here provide a general view of how consumption hotspots drive global emissions and to identify patterns, similarities, and clusters, but to compare the CFs of individual cities or to track how a city's footprint evolves over time, more detailed accounts based on local data and standardized measures are needed.

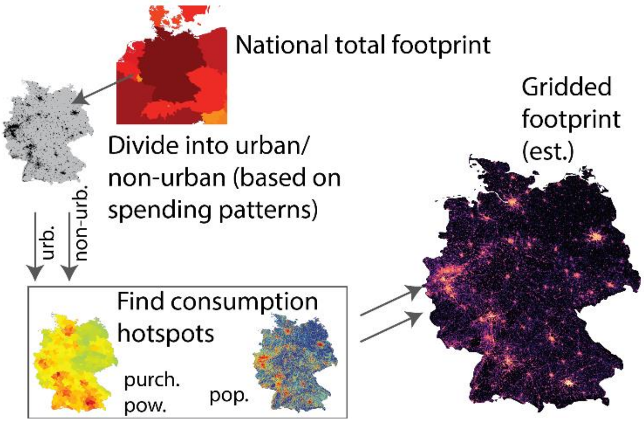

Figure SI.1.1: Illustration of method for gridded model of carbon footprints. The national total footprint is split in to urban and non-urban components based on relative spending patterns, then spatialized using purchasing power and population. This approach is comprehensive and consistent globally but cannot substitute or individual city footprint accounts based on local data.

Urban and rural growth rates are from the UN Population Division (UN Department of Economic and Social Affairs Population Division 2015).

City-level GDP and climate data were taken from the G-econ 4.0 gridded GDP database (Nordhaus 2006). This dataset is provided at 1° resolution and was projected to the Mollweide equal-area projection and resampled at 250m resolution.

Direct emissions are from the spatial FFDAS emissions model (Asefi-Najafabady et al. 2014; Rayner et al. 2010). (We note that gridded emissions models are also available from CDIAC (Andres et al. 2016) and the EU JRC/EDGAR database ((PBL) 2015)).

The MB-International purchasing power dataset refers to the disposable income (i.e. income after taxes and social contributions, including received transfer payments) of a certain region's population. Consequently Purchasing Power consists of net incomes from employment and assets (after taxes and social contributions), pensions, unemployment benefits, benefit payments and other national transfer payments. MB-Research uses information from national or regional state agencies on regional income distribution in the form of tax statistics as far as available. Indicators corresponding highly to incomes (wages and salaries, household equipment and endowment, demographics, unemployment etc.) are also compiled and used for purchasing power calculation by means of statistical methods. Purchasing Power data are computed as current year forecasts. For this purpose income projections are carried out with the help of macroeconomic data and statistic indicators for regions.

Included Subnational CBA accounts

For the USA, Europe, UK, Japan, and China, existing subnational carbon footprint models were used. For these regions, the total national footprint reported by Eora was apportioned to the subnational regions using the state-level weights from these models. The subnational regions were then treated as individual countries in the main model.

Country/Region	Level of detail	Reference
USA	31,531 ZIP codes	(Jones & Kammen 2014)
China	30 provinces (Note that Xizang/Tibet is not included, so national average CF/cap was assumed)	(Wang et al. 2015)
Japan	47 prefectures	(Hasegawa et al. 2015)
Europe	178 mixed NUTS level 1/2/3 regions covering 20 EU countries (Austria, Belgium, Bulgaria, Cyprus, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Malta, Poland, Romania, Slovakia, Slovenia, Spain, Norther Ireland)	(Ivanova et al. 2017)
UK	408 Local Administrative Districts covering England, Scotland, and Wales. Note: Data for Northern Ireland were excluded as the administrative districts have shifted since the study was conducted and digital boundaries for the old districts are no longer available; instead Northern Ireland was taken as a single region from the Ivanova EU model.)	(Minx et al. 2013)

National Carbon Footprints

Carbon footprints for nations were calculated using the Eora multiregional input-output database (MRIO) using the standard Leontief demand-pull environmentally-extended input-output. National total footprints were taken from the year 2013, the most recent year available.

The calculation of carbon footprints using an MRIO database is described in many papers, including (Kanemoto et al. 2016; Peters et al. 2011; Kanemoto et al. 2012; Wiedmann 2009). The Eora MRIO is available online at worldmrio.com and is described in (Lenzen et al. 2012). To calculate per capita footprints we consider gross final demand in each country, not just household final demand, i.e. inclusive of government purchases and change in inventories. Footprints are of Kt CO_2 emitted from fossil fuel combustion.

We assume that direct emissions from households (which importantly includes heating and vehicle fuel) are homogenous nationally. Carbon footprints associated with capital formation are allocated evenly per capita nationally. Both of these assumptions were made for lack of superior information suitable for a global model.

Spatially explicit purchasing power dataset

This dataset was licensed from the market intelligence firm MB International (www.mbi-geodata.com). Per MBI's definition, "Purchasing Power describes the disposable income (income without taxes and social security contributions, including received transfer payments) of a certain area's population." MB International collects this information from surveys and census data. Values are in Euros per capita and are for the year 2015. Note that this layer is only used for spatial distribution within a region. As seen in (Fig. SI.1.2) the level of spatial detail varies worldwide, with data only at the national or state level (e.g. for Singapore and Libya) for some, but at more detailed administrative regions in many countries. In total the data covers 20,159 regions globally (Fig. SI.1.2).

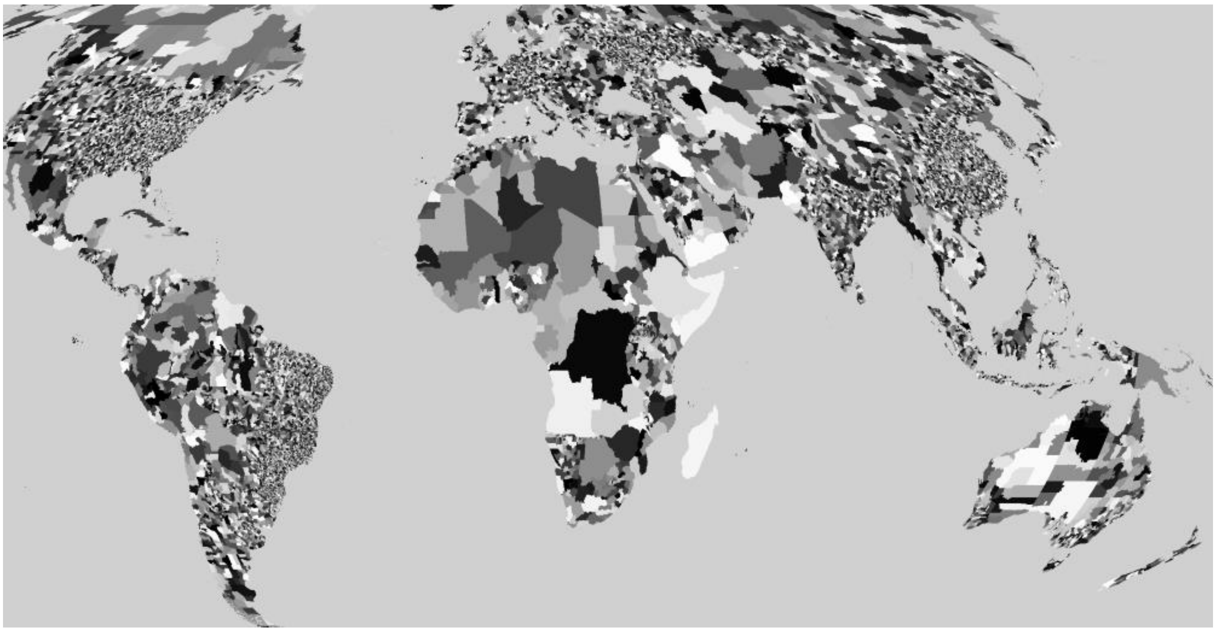

Figure SI.1.2: Illustration of the spatial detail of the purchasing power dataset. This image does not illustrate actual values; all values are randomized to protect the purchasing power data, which were licensed for use but not redistribution. It is provided just to show the degree of spatial detail.

Household Consumer Expenditure Patterns

Consumption expenditure pattern data differentiating rural and urban residents was available for 113 of the 189 countries considered (representing 81% of the total global CO_2 footprint). Three data providers were used. Data were for year 2015 unless otherwise noted. The details about each of the three data sources are as follows:

World Bank (88 countries)

Source: Household Consumption 2010 by Country, Sector, Area, and Consumption Segment, in US$ (Million). Collected by the World Bank from multiple national household expenditure surveys. See

World Bank metadata for sources. The data are available via the World Bank Global Consumption Database http://datatopics.worldbank.org/consumption/detail Accessed September 5 2016.

The World Bank data uses a 12-sector consumption expenditure classification. This was mapped to the Eora26 26-sector expenditure classification as detailed in **SI.2.5 - MoranCEX2Eora26.xlsx**. In future iterations of the model it will be possible to slightly improve resolution by transitioning to the heterogeneous classification structure of the full Eora model, though this involves considerable more researcher time.

EUROSTAT (EU member states)

Source: Structure of consumption expenditure by degree of urbanisation (COICOP level 2) (1 000). URL: http://ec.europa.eu/eurostat/web/products-datasets/-/hbs_str_t226 Accessed September 5 2016. Supporting metadata: http://ec.europa.eu/eurostat/cache/metadata/en/hbs_esms.htm

EUROSTAT data uses the 2-digit COICOP consumption expenditure classification. This was mapped to the Eora26 26-sector expenditure classification as detailed in **SI.2.5 - MoranCEX2Eora26.xlsx**.

US Bureau of Labor Statistics (USA)

Source: US Bureau of Labor Statistics, Consumer Expenditure Survey, Expenditure Share Tables 2011, "Housing tenure and type of land area." URL: http://www.bls.gov/cex/csxshare.htm Accessed September 5 2016.

The BEA consumption expenditure categories were re-mapped to World Bank consumption categories as detailed in **SI.2.4 - US-BEA2MoranCEX.xlsx**, then mapped to the Eora26 consumption categories as per the World Bank data.

For the following remaining 76 countries, accounting for 19% of the global carbon footprint, no consumption expenditure data that separated between rural and urban residents was not readily available. Therefore, for these countries it was assumed that urban and rural citizens have the same spending patterns.

> Algeria, Andorra, Angola, Antigua, Argentina, Aruba, Australia, Bahamas, Bahrain, Barbados, Belize, Bermuda, Botswana, British Virgin Islands, Brunei, Canada, Cayman Islands, Central African Republic, Chile, Costa Rica, Cuba, Cote d'Ivoire, North Korea, Dominican Republic, Ecuador, Eritrea, French Polynesia, Georgia, Greece, Greenland, Guyana, Haiti, Hong Kong, Iceland, Iran, Israel, Japan, Kuwait, Lebanon, Libya, Liechtenstein, Macao SAR, Malaysia, Monaco, Myanmar, Netherlands Antilles, New Caledonia, New Zealand, Gaza Strip, Oman, Panama, Paraguay, Qatar, South Korea, Samoa, San Marino, Saudi Arabia, Seychelles, Singapore, Somalia, South Sudan, Sudan, Suriname, Switzerland, Syria, Taiwan, Trinidad and Tobago, Tunisia, Turkmenistan, UAE, Uruguay, Uzbekistan, Vanuatu, Venezuela, Zimbabwe.

Population Density Map

A gridded population dataset was used from the EU JRC Global Human Settlements – Population Layer (GHS-POP), a global population database with 250m^2 resolution (Freire et al. 2016; PESARESI Martino et al. 2016). The database is for year 2015. Like the purchasing power layer, this layer is used for spatial distribution within a country.

Defining "Cities"

To define "cities" in the analysis, the EU Global Human Settlements Layer Urbanization Model, GHS-SMOD (Pesaresi & Freire 2016) is used . This defines "High density urban clusters" (cities) and "low density urban clusters" (towns and suburbs). High Density clusters (HDC) are defined as "contiguous cells (4-connectivity, gap filling) with a density of at least 1 500 inhabitant/km2 or a density of built-up greater than 50%, and a minimum of 50 000 inhabitants." Low density clusters (LDC) are "Clusters of contiguous grid cells of 1 km2 with a density of at least 300 inhabitants per km2 and a minimum population of 5000." The set of LDCs is a superset of the set of HDCs. Low density clusters include suburbs and smaller satellite communities. In the paper we refer to High Density Clusters as "cities" and low density clusters as towns, and other pixels as rural areas. The GHS-SMOD defines 13,844 cities (HDCs) and a total of 110,180 towns/suburbs (LDCs); this latter figure includes cities.

Distinguishing Carbon Footprints for Urban vs. Rural Households

Consumption expenditure patterns **C** for urban and rural residents ($\mathbf{C_u}$ and $\mathbf{C_r}$) were obtained from consumption expenditure surveys (data sources discussed above). An example is as follows:

	$\mathbf{C_u}$ Urban	$\mathbf{C_r}$ Rural
Shelter	0.5	0.5
Food	0.2	0.1
Transport	0.1	0.2
Other	0.2	0.2
Total	100%	100%

The actual surveys used were detailed to the level of 11-22 household consumption categories, and are provided in the SI workbook.

Next the total expenditure of urban vs. rural citizens was determined using the gridded population datasets $\mathbf{P_u}$ (population in urban, ie. high and low density clusters) and $\mathbf{P_r}$ (population in all other grid cells), and the spatial purchasing power dataset:

Gridded national urban expenditure $\mathbf{X_u} = \mathbf{P_u} \odot$ purchasing power per capita

Gridded national rural expenditure $\mathbf{X_r} = \mathbf{P_r} \odot$ purchasing power per capita

where the $\odot$ operator denotes elementwise multiplication. The purchasing power layer was rasterized from its native vector format to a raster resolution matching the population layer.

Summing these gridded maps one may obtain total urban and rural spending. The ratio of these is taken so that total urban spending is $\mathbf{S_u = X_u ./ (X_u+X_r)}$ and total rural spending is $\mathbf{S_r = X_r ./ (X_u+X_r)}$. To continue with the example:

Total national urban spend $\mathbf{S_u}$	Total national rural spend $\mathbf{S_r}$
4	1

The total urban spending $\mathbf{S_u}$ was then disaggregated by multiplying by the urban consumption pattern vector $\mathbf{C_u}$. The same was done for rural spending.

The total national carbon footprint provided by Eora was then aggregated to the 12 sector classification using the aggregation table provided in SI.2.4, then split between the urban and rural residents based on these two vectors of total rural and urban spending. Using the current example the vectors calculated as $\mathbf{C\hat{S}}$ (where ^ denotes diagonalization) were used to disaggregate the Eora26 carbon footprint between urban and rural residents.

Total national carbon footprint, from MRIO:

	Urban Share
Shelter	10
Food	6
Transport	4
Other	2
$\sum$	22

Pro-rating vectors ($\mathbf{C\hat{S}}$):

	Urban Share	Rural Share
Shelter	2.0	0.5
Food	0.8	0.2
Transport	0.4	0.1
Other	0.8	0.2

National carbon footprint, urban vs. rural:

	Total	Of which urban	Of which rural
Shelter	10	8	2
Food	6	4.8	1.2
Transport	4	3.2	0.8
Other	2	1.6	0.4
$\sum$	22	17.6	4.4

From this the per capita urban and rural footprints in each country may be calculated (Fig. SI.1.3).

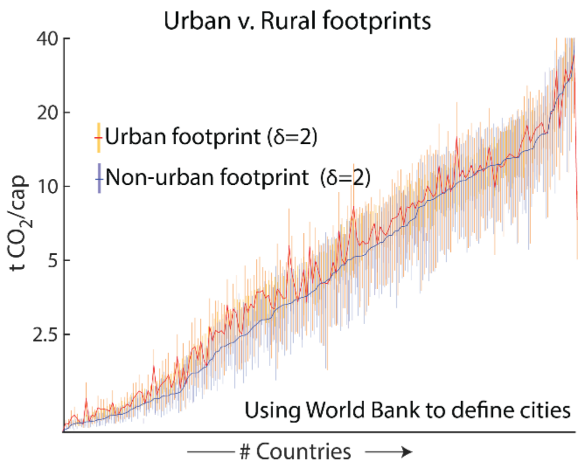

Figure SI.1.3: Urban and rural footprints per capita, by country, sorted by ascending average rural footprint. There are 189 countries. The uncertainty bars show the two-standard deviation range from the Monte Carlo analysis.

The model results suggest that urban residents have slightly higher footprints per capita than non-urban residents, however there is high variance with the two groups (see Sensitivity analysis below) so no clear difference between urban and rural per capita footprints can be stated in a statistically significant manner in our model. (Gill & Moeller 2018) studying Germany also found that the difference in household CF between village and urban center households is not so stark.

While the model is informed by regionalized purchasing power and the different urban vs. rural spending pattern, overall a correlation is observable between urban population per country and urban CF per country (Fig. SI.1.4).

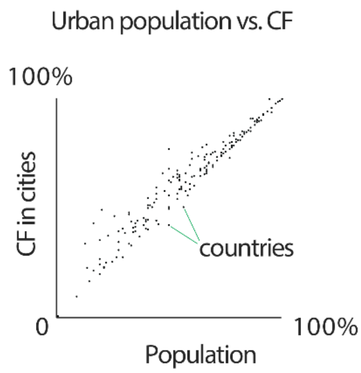

Figure SI.1.4: CF and population in urban areas, per country. Countries with less urbanized populations (urbanites as percent of total population, x axis) tend to have more CF driven by cities (y axis), possible reflecting greater inequality in less urbanized countries.

Sensitivity analysis

There are a number of sources of uncertainty in the model and necessary assumptions made. We did not attempt to assess the reliability of the data and models used as inputs, but we did attempt to assess the sensitivity of our model to the assumptions made within. Assessing the carbon footprints of individuals, households, and cities is complex, and sources of uncertainty include:

1. The relative carbon intensity of equivalent expenditure in urban vs. rural areas is not equal, e.g. $1 of expenditure in a product category in urban vs. rural areas is equally carbon intensive
2. Direct emissions from households, which importantly includes heating (or district heating) and vehicle fuel, are not consistently attributed. Additionally, rent sometimes includes heating expenses.
3. Carbon footprints associated with government purchases, change in inventory, and capital formation are currently allocated evenly to all households evenly per capita; it is also possible to attribute this by another attribution principle.

While a sensitivity analysis of the entire model across all of these error categories is computationally prohibitive it is possible to make reasonable inferences about the confidence of the results at the grid cell level. We take errors of the national and subnational (for those regions where subnational regional models are available) total footprints, as well as gridded population data as given and concentrate on those errors we add on top through the distribution of CF.

To construct the range of alternative global Lorenz curves (shown in Figs. 3 and 4) a Monte Carlo procedure was employed. The total carbon footprints per grid cell were randomly drawn from a normal distribution using mean μ_i equal to the original CF estimate and two different scenarios for variance σ_i^2, where i denotes a grid cell. In Scenario 1, σ_i^2 is specified such that the standard deviation relative to the mean $\sigma_i/\mu_i = 1$, whereas in Scenario 2 $\sigma_i/\mu_i = 10$. The carbon footprint per grid cell was constrained to a lower limit of 1% of the original estimate to prevent negative values. The resulting CFs were then normalized within each country or subnational region to sum to the respective totals provided by the models we used as an input to our model. Lorenz curves were constructed for each perturbation scenario. It is noteworthy that almost all of the alternatives scenarios (100 monte carlo runs) resulted in a more unequal distribution of carbon footprints than the original estimate, as shown by the uncertainty ranges lying mostly above the base Lorenz curves.

The variance of individual city CFs was calculated in a similar manner. All urban cells within a country were assumed to have a C_V=1.0, and the total rural footprint in a country also assumed to have a C_V=1.0, to allow for uncertainty around the split of footprint into urban and rural components. These sampled values were then rescaled to match the national total footprint, which itself also sampled from a normal distribution. Informed by previous work investigating the reliability of MRIO-based carbon footprint results (Moran & Wood 2014) the countries were assumed to have a C_V=0.25. The total CF for each city was calculated during each perturbation, and the variance of the city CF was calculated from the set of these results.

Urban and Rural Growth Rates

Annualized urban and rural growth rate forecasts for Fig. 3 were taken from the UN World Urbanization Prospects, 2014 Edition report (most recent edition) (UN Department of Economic and Social Affairs Population Division 2015) by calculating the annualized growth rate between the forecasted urban and rural population of each country in 2020 and 2050 (Tables F03 and F04). Within each country urban and rural growth rates are homogenous, i.e. do not distinguish between different cities or rural areas within a country.

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