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## Spatial variation in household consumption-based carbon emission inventories for 1200 Japanese cities

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## LETTER

# Spatial variation in household consumption-based carbon emission inventories for 1200 Japanese cities

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Supplementary material for this article is available [online](#)

## Abstract

Given that national pledges are likely insufficient to meet Paris greenhouse gas (GHG) reduction targets (Fawcett *et al* 2015 *Science* **350**), increasingly actors at the city and state level are looking for options on how local government can contribute to reducing GHG emissions. For a typical city only one third to half of their carbon footprint (CF) is emitted within the jurisdiction, while the majority is embodied in goods and services flowing into the city. To support well-informed mitigation efforts, administrators need robust inventories of both direct emissions as well as the supply chain emissions. Here we construct household CF inventories for 1172 Japanese cities using detailed consumer expenditure data and a Japanese domestic multi-regional input-output (MRIO) model. We identify the consumption activities which city policymakers can target to reduce CF. We observe a strong concentration of household CF in a few cities in Japan: 40% of the total Japanese CF is driven by 143 cities. Understanding a city's consumption-based CF of households in addition to its direct emissions exposes additional policy options for each citizen to contribute to achieving national goals.

## 1. Introduction

Cities are the heart of economic development, and those in cities depend on supply chains bringing goods and services into cities. In modern society there is often a substantial spatial distance between production and consumption places.

While greenhouse gas (GHG) emissions associated with production are directly emitted by producers, consumers share responsibility for emissions given that it is their demand which induces those emissions. Responsibility for emissions is attributable to both producers and consumers [2–4]. Emissions accounts which attribute emissions to producers are called production-based accounts (PBA) emissions, and accounts which follow those embodied emissions through trade and transformations stages to attribute them to final consumers are called consumption-based accounts (CBA), or carbon footprint (CF) accounts. Many studies have prepared CBA accounts of national [5–9], regional [10–13], and city

carbon emissions [14]. Most of these studies focus on national level footprints because of insufficient data of input-output (IO) tables, which calculate the embodied emissions in various good and services, and consumption statistics at regional and city scale.

Cities are emerging as leading actors in climate change mitigation. According to the Carbon Disclosure Project, 1106 cities have set emission reduction targets [15]. Many of these targets consider only direct emissions (PBA) within the city's immediate area. Thus there is a risk that cities may appear to achieve their targets simply replacing products made in the city with products made elsewhere. This phenomenon occurs at the national level. Many countries have made progress toward targets when using conventional PBA accounting, but after including embodied emissions in net trade, their CBA footprint reveals their emissions footprint to be merely displaced, not reduced [5–8, 16].

Larger cities are beginning to evaluate their full CBA emissions footprint. A recent C40 report

estimated the consumption-based carbon emissions of 79 large cities [17]. Yet conducting a rigorous CBA account for a city remains a laborious and data intensive exercise. Many smaller and midsize cities lack any CF accounts and thus have no effective way to measure the climate impacts their consumption drives.

While local authorities clearly can more easily govern the emissions which arise from directly within their jurisdiction (direct emissions), understanding their induced emissions footprint beyond their strict jurisdictional scope can expose new policy options for reducing their total footprint. Put another way, considering CBA-based emissions exposes more opportunities to effect GHG emissions reductions than are available when looking at PBA (also called Scope 1) interventions alone. Local governments can reduce their CF through measures [18] such as:

- not encouraging air travel
- encouraging plant-based diets, e.g. supporting farmers markets, vegetarian-first layouts at public canteens, or promoting meatless Mondays
- requiring certified renewable electricity
- promoting electrical or hydrogen refill stations and fleets, and restricting fossil fuel and energy inefficient vehicles
- requiring environmental product declarations in building materials
- adopting green procurement

Four of the authors of this paper live in cities where municipal solid waste is sent away to an incinerator outside the core city jurisdiction: implementing carbon capture at that facility would offer a substantial GHG emissions reduction yet this reduction opportunity might not be visible in simple within-city-limits direct emissions. Existing studies estimating city CFs predominantly use one of two methods: top-down estimates which using city-level purchasing power and population data to decompose national or state level estimates into constituent cities in the region [19] or bottom-up methods which build on consumer expenditure data [20–27]. The bottom-up approaches tend to be more accurate but are far more data intensive and require consumer expenditure data at the city or household level. Top-down approaches seek to estimate CFs for many cities in an area at once and use estimation where city-level emissions and expenditure data is inconsistent or missing. Yet top-down studies most often do not use city-level detailed consumption categories and thus are not as accurate as those built using a bottom-up approach. As a hybrid between the two there are several studies which use city-level IO tables [28–31], detailing economic flows, production, and consumption at the city level. However, statistical agencies do not usually compile city-level IO tables. One project, the Industrial Ecology Virtual Laboratory (IELab) estimates

city-level IO tables to construct a city-level multi-regional input-output (MRIO) model [32]. A IELab version for Japan has recently been announced [33].

In this study we integrate a 47 prefecture MRIO model of Japan with microdata from 60 000 households itemizing consumption expenditure and estimate consumption-based emission of 1172 Japanese cities. We also explore the relationship between per capita city-level CF and population density and expect a positive slope. This hypothesis is based on the fact that in Japan the more densely populated places have higher incomes. Using this, we identify which consumption activities policymakers should target to reduce consumption-based emissions.

## 2. Data and methods

We estimate the consumption-based carbon emissions of 60 000 households using an MRIO model which covers Japan's 47 prefectures and includes trade. The MRIO table is from Hasegawa *et al* [10]. We collected direct carbon emissions from each prefecture, itemized by industry, by contacting each prefecture's official environmental division (see table S1, available online at <https://stacks.iop.org/ERL/15/114053/mmedia>) and using prefecture-level energy balance tables [34]. The energy balance tables contain energy use by fuel types and industries, carbon intensities by fuel, and detailed carbon emissions by industries but lack the emissions from most transport industries. To correct these emission datasets, we use official carbon emissions (broken down into five sectors: industries, commercial, residential, transport, and energy conversion) totals as scale and itemized carbon emissions from energy balance tables (31 sectors) to disaggregate official total carbon emissions amongst all industries. Therefore, we consider the energy carrier difference by prefectures and the fuel mix. We contact and collect prefecture-level official carbon emissions from environmental division of each prefecture (see table S1 and figure S4). The energy balance tables lack most of transport industry (only private household transport is available) and therefore we complement it with officially compiled emissions by prefecture. In this study, we only consider carbon emissions and does not include other GHG emissions. To inform the structure and level of consumption data we use the original micro-consumption data from the 2004 National Survey of Family Income and Expenditure (NSFIE) conducted by the Statistics Bureau of Japan. The survey provides the aggregated version of household consumption data in their website. For this study, we used the household-level microdata results from ~60 000 households with 321 consumption items, obtained by special permission. The data sampling and collection of household expenditure survey was carried out by the Statistics Bureau of Japan with stratified sampling (see

[www.stat.go.jp/data/zensho/2004/cgaiyo.html#5](http://www.stat.go.jp/data/zensho/2004/cgaiyo.html#5)). In this analysis we focused on household emissions and do not include consumption by non-profit organizations, government consumption and capital formation. Although our analysis does not cover whole city's CF, CF from household consumption is dominant for the total CF on the globe [35], and the Japanese household CF consists of 60% of the total [36]. Note we needed to use 2004 NSFIE dataset because there is no publicly available newer version of 47 prefecture-level MRIO after Hasegawa et al [10]. MRIO and emissions data are for 2005.

The consumption-based carbon emission of household  $h$  in city  $k$  attributed to prefecture  $s$  is defined as [4, 37]:

$$F_{jh}^k = \sum_{i,r,s} f_i^r L_{ij}^{rs} y_{jh}^{k,NSFIE} \quad (1)$$

where  $f$  refers to factor inputs, i.e. GHG emissions per unit of production,  $L$  is the Leontief inverse (see [38] for more information about the use of the Leontief demand-pull model for calculating CFs),  $y_h^{k,NSFIE}$  is consumption expenditure of each of the 60 000 households in city  $k$  reporting in the NSFIE,  $i$  and  $j$  are sector of origin and destination, and  $r$  and  $s$  are the exporting and importing prefectures, respectively. We converted the consumption expenditure data from purchasers' price into producers' price using margin and producers' price final demand of national IO table.

Based on these footprints as estimated for each of the 60 000 individual households we estimate the city household footprints as follows.

Because consumption data for a whole city is not available for each city, we estimate the consumption-based carbon emission of cities by CF per capita  $\times$  population. Each city reports the number of residents living in single-person, two-person, and 3+ person households. We assume that all persons in a city in a single-person household follow the mean consumption pattern (i.e. expenditure per category) of single-person sample homes in that city; all persons in a city in a two-person household follow the mean consumption pattern of two-person sample homes in that city; and so on. All samples are given the same weight, as there is no information available which would suggest that one sample represents more households than another sample. In the cases where we have  $<5$  samples for that household type in that city, we assume the households of that type in that city follow the prefecture-average consumption pattern. This is admittedly a simplistic assumption, but so far no studies estimate consumption-based city emissions by expenditure category, so this approach represents a first step, albeit with higher uncertainty. Formally, we use following method to estimate consumption-based carbon emission of

city  $k$ :

$$F_j^k = \sum_t F_j^{k,t} \quad (2)$$

$$F_j^{k,t} = \begin{cases} \overline{\sum_{h=1}^{m^{k,t}} F_{jh}^{k,t} / \sum_{h=1}^{m^{k,t}} n^h P^{k,t}} & (m^{k,t} \geq 5) \\ NA & (otherwise) \end{cases} \quad (3)$$

where  $t = \{one - person, two - person, more than three - person\}$  is family type,  $n^h$  is the family size of household  $h$ ,  $m^{k,t}$  is the number of households for each city  $k$  and family type  $t$ ,  $P$  is the city population, and  $\bar{\phantom{x}}$  is sample mean. NSFIE database also provide the number of persons for each household and therefore we can also get household-level CF for each family type,  $F_h^{k,t}$ . If data are available for just one home type, we use equation (4) to estimate consumption-based emission of other family types for absolute volume and just use available household type for per capita.

$$F_{j^{IO}}^{k,t} = \overline{F_{j^{IO}}^s / P^s} P^{k,t} = \sum_{i,j,r} f_i^r L_{ij}^{rs} y_{j^{IO}}^s / P^s P^{k,t} \quad (4)$$

where IO refers that the source is from MRIO. Cities with insufficient data ( $<5$  microdata entries for every family type) are shown in grey in maps and reported as insufficient data in our results. We can estimate all (2300) city-level household CF with insufficient data using equation (4) and show in figure S1 but do not mention in main text because of much higher uncertainty. Thus, the number of cities with household CF shown in the main text is 1172. We get the number of persons in each family type in each city from a national census in 2004. The city polygons/boundaries are retrieved from Kirimura et al [39] (<http://tkirimura.com/mmm/>) and used for figures 1, 4–6, S1, S2, and the website. Because NSFIE's and IO table's classification is different, we apply the concordance table (see the supporting information: SI) to match the classification from 321 items to 80 commodity sectors and provide the results at 11 aggregate sectors.

In figures 4–6 and table 1, we estimated relative deviation from the mean of per capita consumption-based emission for Japanese households as follow:

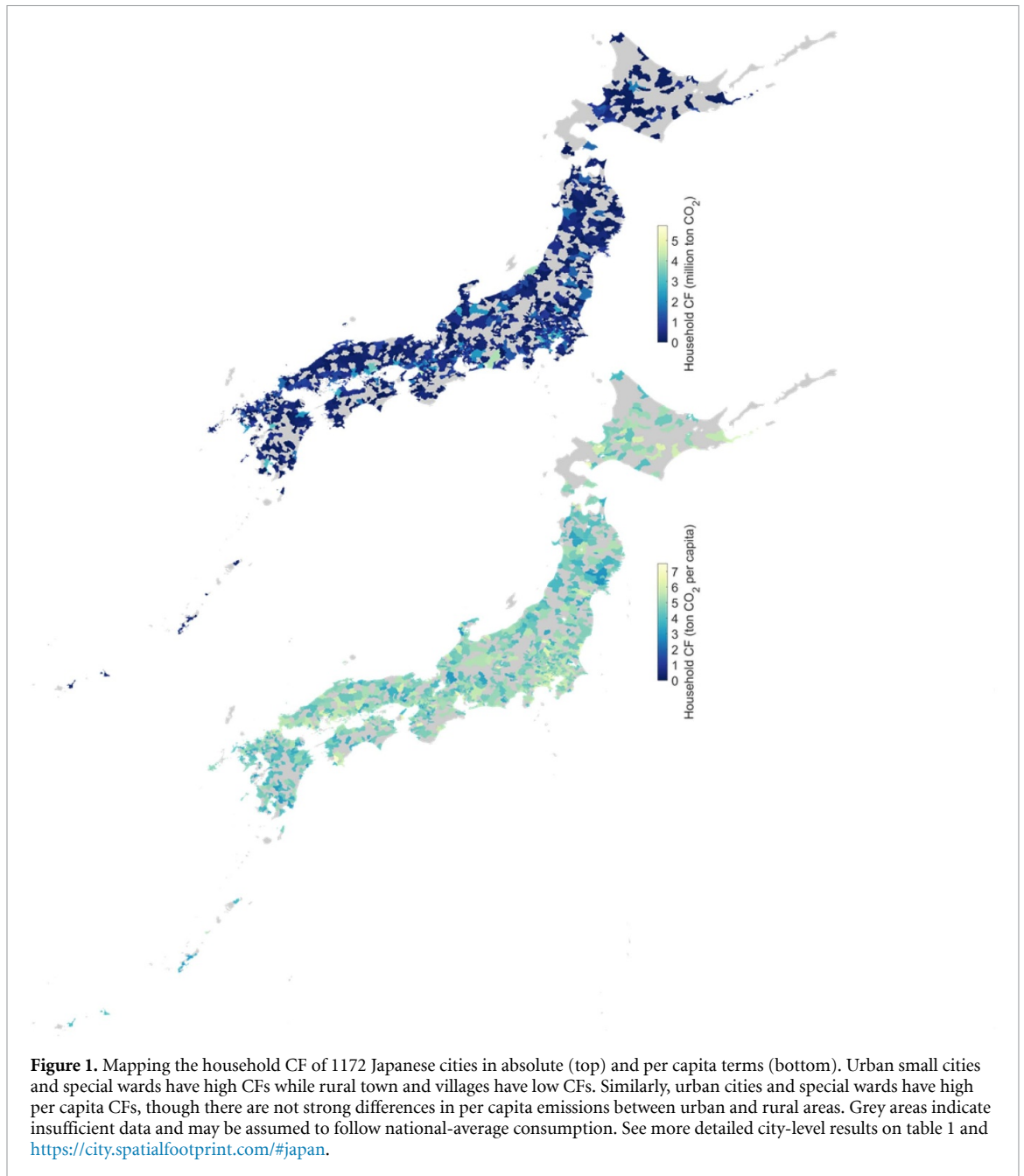
$$D_j^k = \frac{F_j^k / P^k}{F_j / P} - 1 \quad (5)$$

where the denominator shows the Japanese average per capita CF and the numerator shows the city-level average per capita CF.

Uncertainty is introduced into the results from two sources. First, the MRIO model used to calculate CBA accounts for regions and individual products is not perfectly reliable. Second, the city-level results may be subject to sampling error, i.e. that the

Table 1. City household CF per capita, as difference from national average, for selected cities.

	Public Transport	Private Transport	Other Services	Other Energy	Medical Care	Gas	Food	Electricity	Education	Durable Goods	Consumable Goods	All
Higashi, Sapporo (Hokkaido)	72.8%	-22.5%	10.8%	96.5%	0.7%	33.0%	14.1%	-12.9%	-61.1%	26.0%	17.9%	11.0%
Kushiro (Hokkaido)	6.2%	19.0%	17.3%	232.0%	29.8%	-8.0%	8.1%	-5.1%	86.6%	-1.1%	5.5%	18.6%
Hirosaki (Aomori)	-29.9%	-18.4%	-19.0%	363.0%	5.2%	-14.9%	-7.5%	-9.6%	-10.9%	-16.0%	-14.9%	-4.2%
Tsukuba (Ibaraki)	39.5%	46.3%	2.7%	-23.9%	14.7%	22.2%	5.5%	-6.1%	28.1%	24.1%	16.4%	17.2%
Setagaya (Tokyo)	240.6%	-52.2%	41.7%	-78.4%	6.1%	30.6%	55.7%	22.2%	-51.4%	184.2%	26.8%	44.7%
Nagaoka (Niigata)	-27.9%	17.2%	4.1%	-6.5%	10.3%	10.5%	3.0%	-7.3%	-30.8%	-12.0%	-11.4%	-1.0%
Matsumoto (Nagano)	36.5%	14.9%	46.6%	90.6%	9.3%	12.2%	8.9%	-6.9%	-30.1%	6.2%	12.9%	17.5%
Chigusa, Nagoya (Aichi)	61.3%	-14.1%	30.6%	-87.5%	76.5%	34.4%	21.2%	8.5%	4.0%	27.3%	-6.1%	15.6%
Fushimi, Kyoto (Kyoto)	84.4%	-25.3%	30.5%	-77.2%	3.2%	36.6%	28.8%	7.2%	-44.8%	35.1%	4.4%	14.4%
Sakai (Osaka)	58.9%	-13.9%	3.5%	-88.7%	20.0%	21.6%	13.7%	7.5%	-27.7%	13.2%	2.0%	4.5%
Izumo (Shimane)	-27.3%	17.6%	-7.2%	-28.5%	16.5%	19.5%	1.9%	2.1%	-29.0%	-16.9%	24.6%	0.7%
Matsuyama (Ehime)	10.1%	-18.0%	20.7%	-4.4%	16.2%	10.8%	9.3%	26.3%	-14.5%	19.3%	18.1%	8.8%
Hakata, Fukuoka (Fukuoka)	54.4%	-10.6%	18.5%	-77.4%	36.3%	60.4%	40.8%	-5.9%	-65.6%	32.3%	0.4%	15.7%
Kagoshima (Kagoshima)	7.8%	1.8%	0.8%	-67.6%	8.6%	34.6%	0.1%	10.5%	18.0%	7.6%	8.4%	4.8%



households surveyed are not perfectly representative. Households may misreport their spending on the consumer expenditure survey, and the households sampled may not be perfectly representative. Regarding the first source of uncertainty, since Japanese MRIO models do not report any standard error information it is not possible to precisely quantify the reliability of the MRIO results. However, based on previous work on reliability and cross-agreement of MRIO databases [40–42] we opted to assume 20% relative standard error (S.E.) and normally distributed error for each data points. Theoretically, uniform relative S.E. is unfavorable, and MRIO tables and emission data should show non-uniform S.E. [40, 43] like the Eora MRIO table. Other studies

have investigated the reliability of MRIO results at the international level and found that independent models agree to within  $\pm 5\%$  for developed economies and  $\pm 20\%$ – $40\%$  for smaller economies [41, 42, 44]. The other source of uncertainty, arising from potential sampling error, can also be estimated quantitatively. We estimated the uncertainty of CF of cities associated with sample size using a bootstrap method. We used following procedures to estimate the uncertainties. First, we performed a bootstrap sampling using 1000 iterations. Second, we chose the size of the sample and use all samples for each city. Finally, we estimated CF of cities from each sample and computed the standard error of CF of cities.

### 3. Results

We show household CF of 1172 Japanese cities in both absolute and per capita terms in figure 1. Household CF of cities range from 0.007 to 6.733 Mt CO<sub>2</sub>, or from 2.4–7.5 tCO<sub>2</sub>/cap. The top decile of highest-emitting cities (117 of 1172 cities) drive 34.5% of Japan's total CO<sub>2</sub> footprint. The top 30% of highest-emitting cities (352 of 1172) drive 64.5% of CO<sub>2</sub> emissions in Japan.

Japan has ~2000 cities in total and this study covers only 1172 cities. We did not analyze the remaining cities since they have either no data or an unusably small sample size (<5 responses). These towns tend to be bedroom communities or small-scale agricultural communities with small direct emissions but standard levels of embodied emissions from consumption.

Before presenting results the reader should know that several large well-known cities in Japan including Tokyo and Osaka are, formally, not single cities but are composed of several 'special wards'. We chose to follow these formal jurisdictions as these align with most of the source data available. In order to be useful to policymakers the results too should follow these formal jurisdictions. For these special wards we note in parentheses the well-known name of the urban area they are part of.

The top 5 cities with the largest CF are Setagaya (Tokyo), Ota (Tokyo), Sakai (Osaka), Hamamatsu (Shizuoka), and Niigata (Niigata). These are concentrated in urban areas. The top ten cities by CF per capita are Nishi (Hokkaido), Musashino (Tokyo), Sukumo (Kochi), Shinagawa (Tokyo), Chuo (Tokyo), Kokubunji (Tokyo), Nakano (Tokyo), Setagaya (Tokyo), Nishi (Saitama), and Bunkyo (Tokyo). We observe some unusual results like high per-capita CBA in the small city of Sukumo (population: 24 000 people, number of household samples: 25) and Minowamachi (population: 26 000 people, number of household samples: 27). As the sample size per city becomes smaller, the probability that the smaller sample correctly represents the entire city decreases. Thus, results for smaller cities are less reliable than results for larger cities. Several figures with further information on dataset and city-level result reliability are presented in the supplementary information.

Japanese cities tend to have more similar CBA emissions but a larger variation in their PBA-based emissions (figure 2). Figure S2 shows city carbon emissions in PBA. Cities with large imports of embodied emissions (CBA exceeding PBA) tend to have high population densities. This is a consequence of the fact that that urban residents rely on power plants, factories, and agriculture located in less dense areas.

Larger cities tend to have higher per-capita CFs. CF per capita grows positively with city size until a size of c. 400 000 (figure 3(a)). We hypothesized

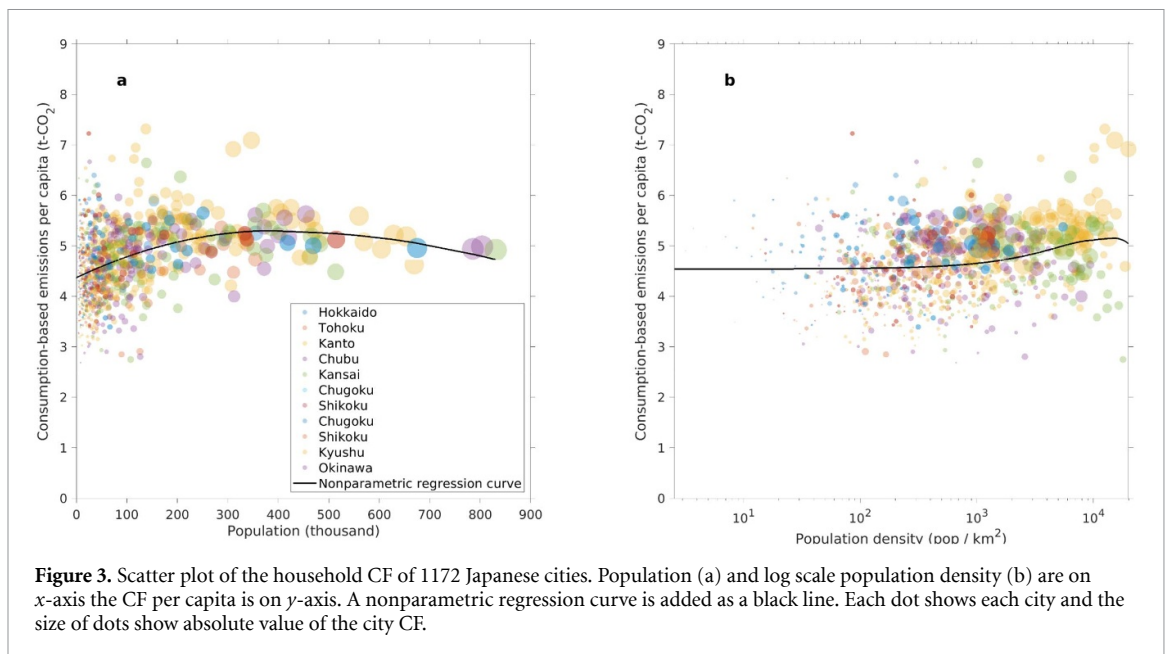
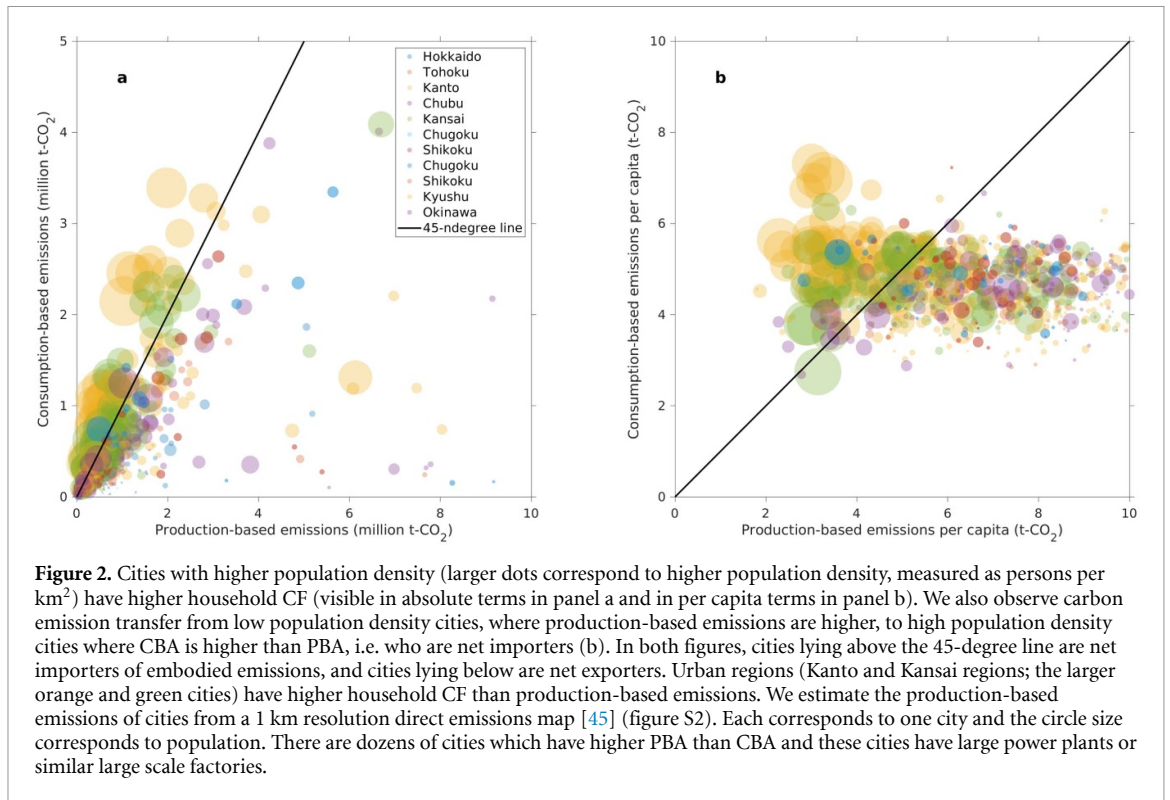
that more dense areas would also have higher CF per capita, but the results show that CF per capita is relatively invariant to density (figure 3(b)). The detailed commodity-level results are different from the overall trends. As population density increases, transport CF per capita decreased (figure S9).

In Japan small and large cities have relatively similar CF per capita, though large cities tend to have slightly higher CF per capita than smaller ones except for >400 000 population cities. Interestingly, this is the opposite of what is observed in Norway. Larsen and Hertwich report that smaller municipalities have a larger consumption-based carbon emissions per capita [46]. This may come from the differences between Norwegian and Japanese lifestyle. Our results for Japan show a large variation in CF/cap for smaller (<200 000 ppl.) cities, with some of these smaller cities being rural and having low income and low levels of consumption.

Figures 4–6 illustrate how various cities differ from the mean pattern of consumption-based emission in Japan. The differences in city-level CBA results means each city will have a slightly different ranked priority order of areas where to work to reduce their footprint.

In figure 4 (top panel) the cities in red have high private vehicle emissions relative to the national average. Metro areas, in blue, tend to have low private vehicle use. Policymakers in cities with high emission from private vehicle use can prioritize policies to address vehicle emissions. The lower panel of figure 4, showing public transport including air transportation emissions relative to the national average, reveals that those same cities with high private vehicle use also under-utilize public transport relative to the national average. (This latter result would also be observed if public transport in rural areas had a lower carbon intensity than public transport in Tokyo, however it is more likely lower level of public transport activity [47, 48], rather than a lower carbon intensity of that activity, which explains this result.) Urban residents use air travel and emit a large CF (figure S6). When public and private transportation are combined, the CF of transportation is relatively greater for residents of suburban areas (figure S7).

Figure 5 highlights cities with above- and below-average per capita consumption-based emission of electricity (top panel) and other energy (mainly kerosene for heating) (lower panel). Note that these energy items are only accounted for the home-related energy and that the CF associated with energy/fuel for private vehicle is considered in private transport sector. For cities with above-average CFs from electricity, the cities in western Japan shown in red in figure 5 top panel, demand-reduction measures and securing low-carbon electricity will be high priorities. For cities with above-average fuel oil footprints,

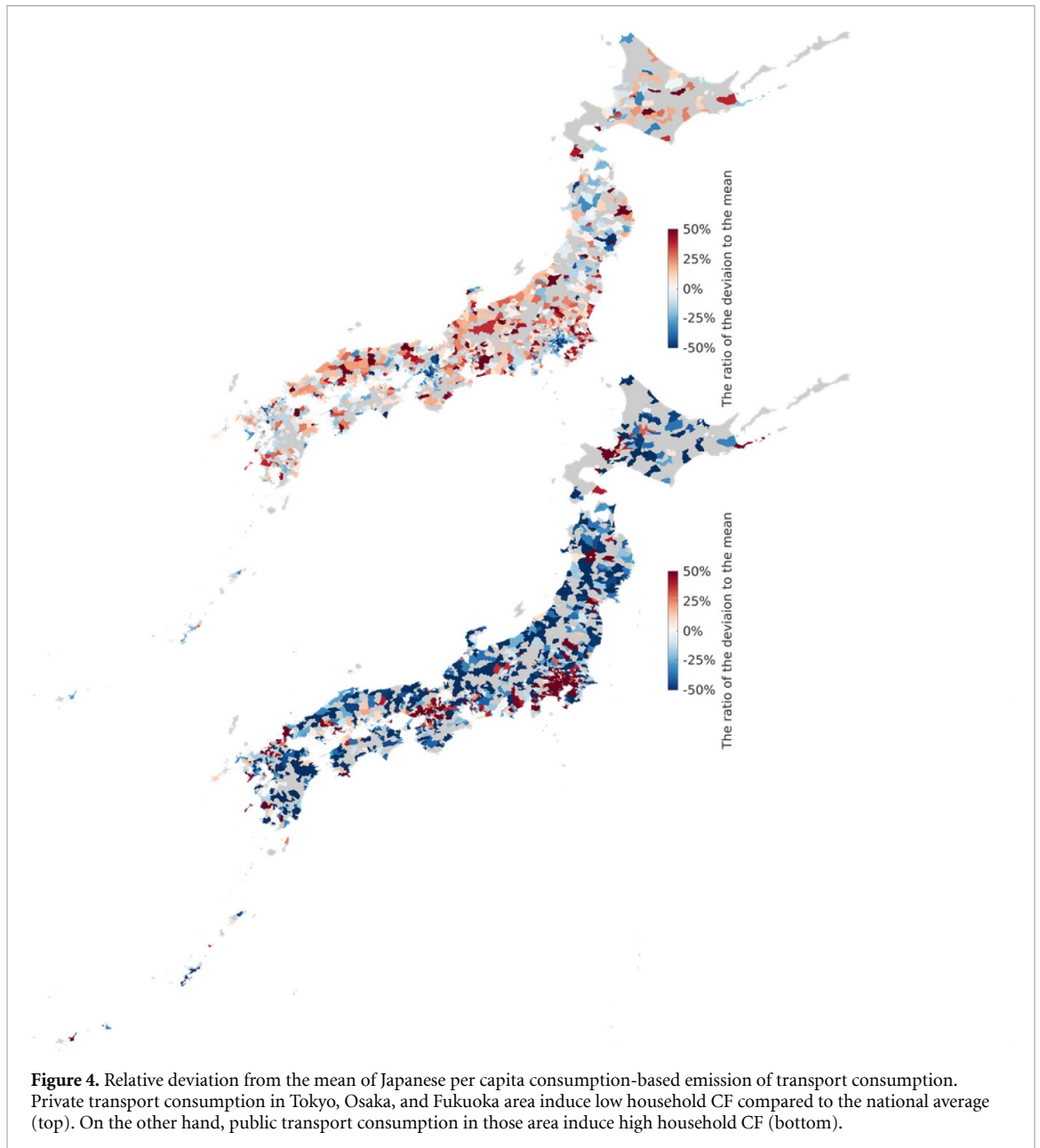


which are shown in red in figure 5 lower panel, reducing non-electricity energy emissions will be more important. (As a reminder, in the MRIO modeling used in this study, direct emissions from building fuel oil emissions will be correctly attributed to the city in both PBA and CBA accounts.). According to the total CF related to all energies (electricity, gas, and other energy), cities in the north, which consume more kerosene for heating, emit more CF than other regions (figure S8). The results also reveal that city residents have higher CFs from durable goods (e.g. personal

computers, TVs, or cars) and food consumption compared to rural areas (figure 6).

Looking selected individual cities, it is clear that individual cities vary in tangible ways compared to national averages. Table 1 presents results from several cities. The cities shown in table 1 were hand-selected to show a range of geographic and demographic variety. Full results for all cities will be made available from the project website <https://city.spatialfootprint.com/#japan>. In the results we can see for example that in the Setagaya



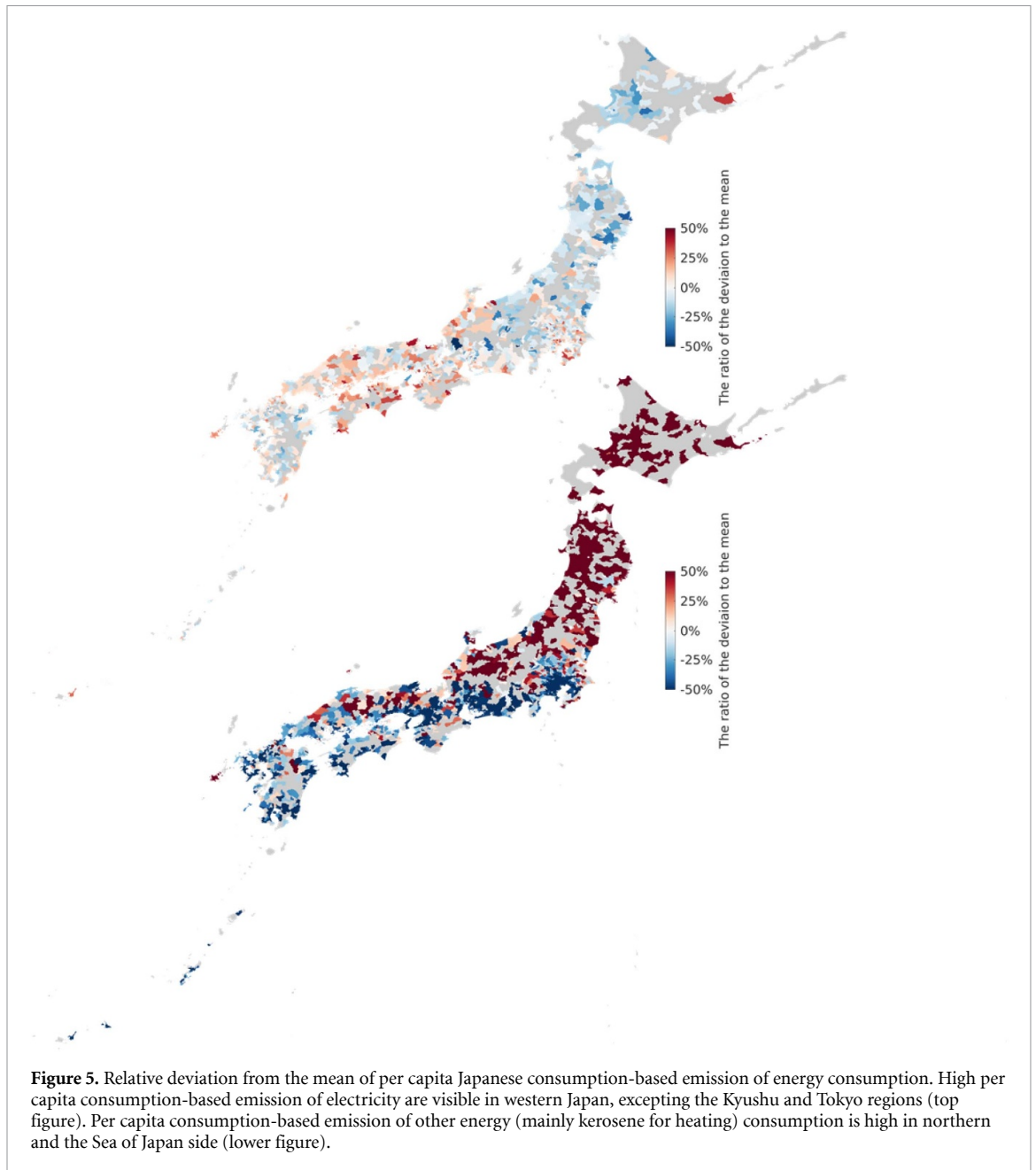


ward of Tokyo, Matsuyama, and Kagoshima electricity usage is higher than the national average. Sustainability practitioners working at the city level can use this result to look into more detail why these cities have above-average electricity usage. Setagaya also has an exceptionally high public transport footprint (240% above the national average). There, efforts to realize low-carbon public transport can have a very large effect in reducing its city household CF. City managers can look more closely into specific categories to learn about relevant policy options. For example, Hakata in Fukuoka has a much below-average CF from education. Authorities there can investigate whether this is due to less education activity in general, or whether the level of activity is normal but the carbon intensity of that activity is advantageously low. The reliability information, based on the uncertainty associated with the sample size, is

shown in figure 7. For example, Higashi, Sapporo, (Hokkaido) emit 1.33 Mt CO<sub>2</sub> (2.5–97.5 percentile: 1.16–1.54 Mt CO<sub>2</sub> or 87.7%–116% compared to our estimate). The range of error highly depends on the number of samples and data variation. A large number of samples and large city have small error range and vice versa.

#### 4. Discussion

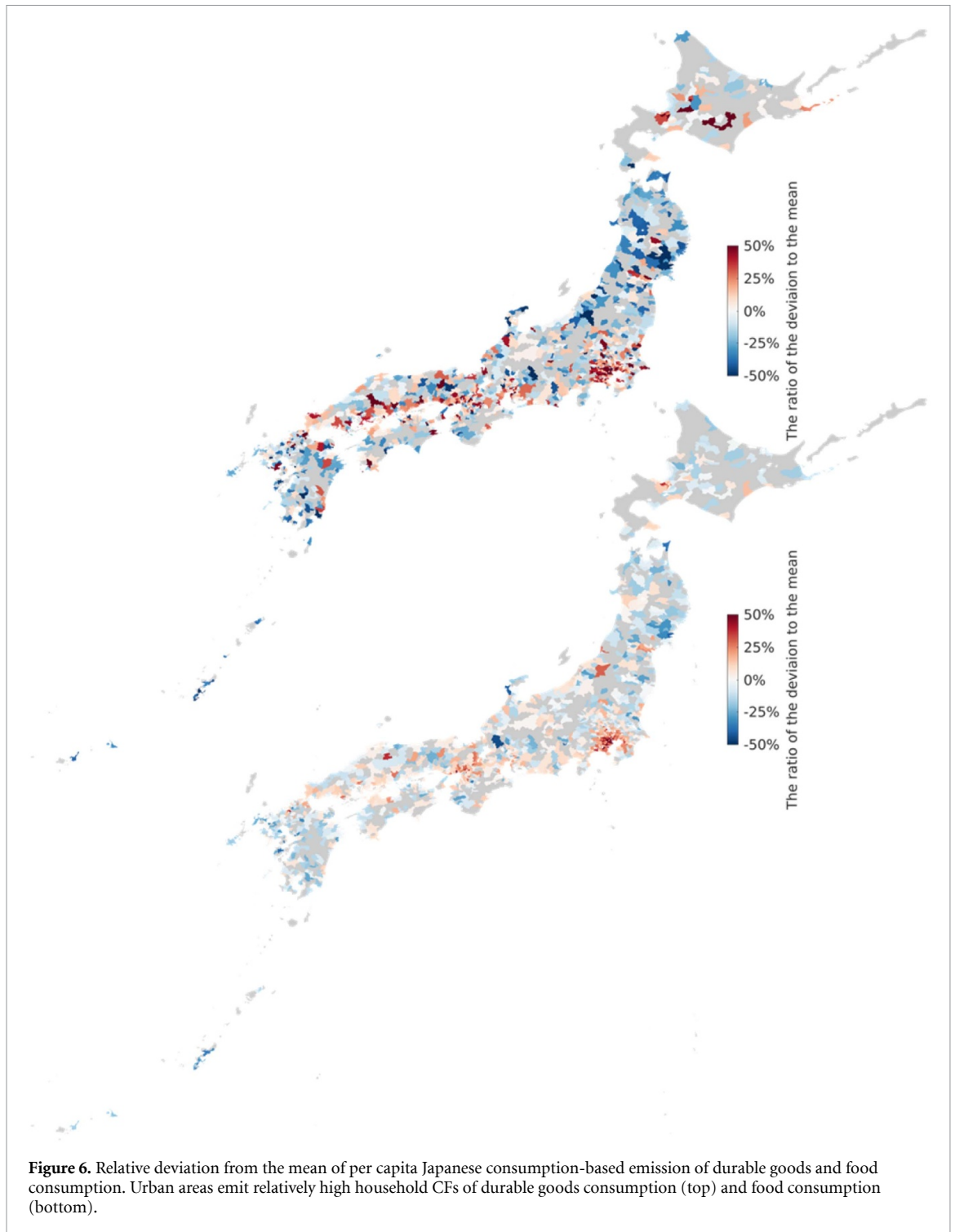
Different cities have different consumption patterns. Information on the composition of the city household CF is necessary for cities to tailor policy options to suit and prioritize the most effective steps to reduce their consumption-based carbon emissions. This study presents for the first time an itemized and comprehensive inventory of city-level household CF inventories estimated using detailed consumer



expenditure microdata. These inventories can be used by cities to complement the direct emissions inventories that are already published by provincial authorities and tailor a climate action plan to suit them. Furthermore, we observe that consumption-based carbon emissions of cities are highly concentrated in a few cities. 143 cities induce 40% of the country's total household CF. This means that strong action by a relatively few cities can have a large impact helping Japan achieve national level climate targets. Climate mitigation actions by a small number of cities can provide substantial reduction of carbon emissions.

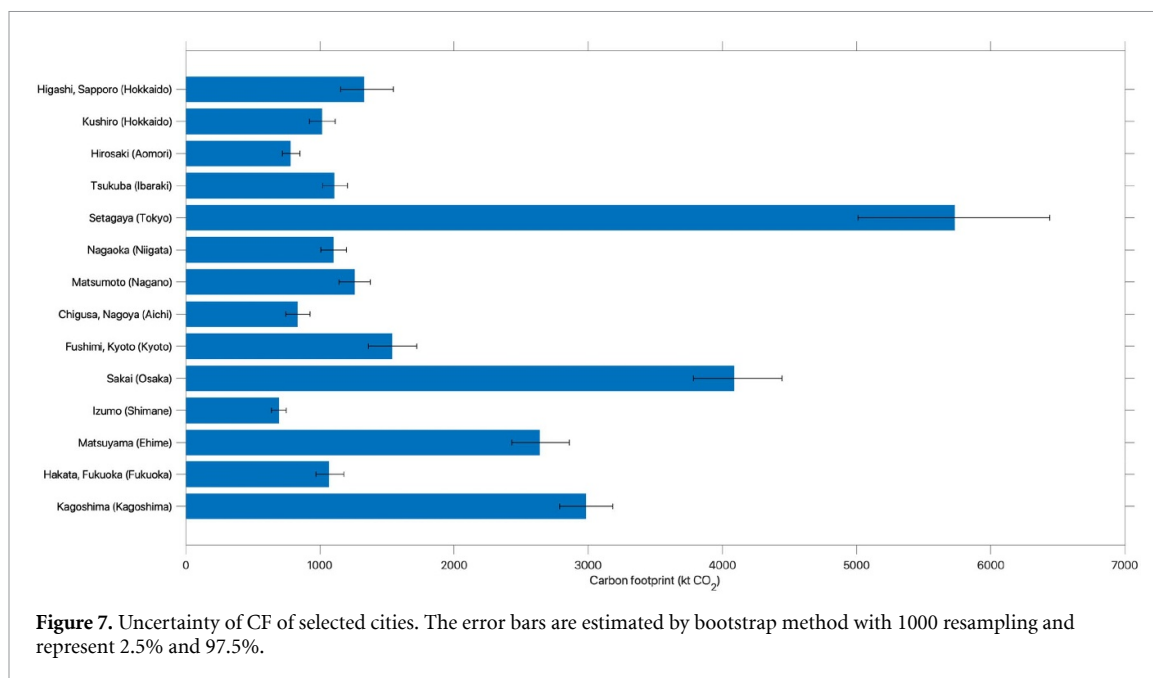
There are two broad kinds of uncertainties in the calculation of CF of cities. One is from the lack of sample size and the other is from data itself. For example, we need to estimate CF of a city from five

samples and can estimate CF of another city from 100 samples. Usually, the latter estimate is much more accurate than the former estimate under random sampling. Even if we get enough samples to estimate CF of cities, collected data is not accurate because of misreporting etc. Because the Japanese prefecture-level MRIO table does not report the standard error, in this study we cannot estimate the later uncertainty correctly method. Only a few environmental footprint studies estimate the uncertainty of the former estimates, but based on indicative findings from Oita *et al* [49] and Lenzen *et al* [50], the uncertainty range of the later may be expected to be around 10%–30%. Another limitation of the present study is that the Japanese MRIO used assumes that goods imported into Japan use the same global carbon intensity regardless of country of origin. Finally,



the data vintage must be kept in mind as a limitation of the results presented here. While consumption expenditure has grown since 2004, the relative expenditure on different categories of goods and various foodstuffs is perhaps more stable. The vintage of the IO table data is also a limitation. In executing this study we faced the choice between an older, year 2005 Japanese MRIO, or a newer, year 2015 IO. We used the 2005 MRIO because city-level CF highly depends on the emission factor by prefecture industries such as

regional electricity producer. The body of MRIO literature has shown that the inter-regional trade flow is only the 3rd or 4th most important item in an error budget [51–53]. The direct emissions data, in-region IO table, and consumption bundle, are more important factors in achieving accurate IO results. The prefecture-level direct emission data is from detailed sectoral level energy balance tables and official direct emissions by prefectures and therefore these factors are well handled in our model.



Finally, we recommend the following three main policy targets. The first is increasing public transport and renewable fuel vehicles. The cities in red in figure 4, upper panel, are heavily reliant on private cars. While in many areas it is not feasible to ask residents to give up cars, providing incentives for electric and renewable fuel vehicles and increased support for public transport could be a powerful emission reduction policy. Second, heating and cooling are one of biggest drivers of household CF, yet any measures have not been taken to reduce those building energy demand regarding differences of the regional characteristics [54]. There is still room for reducing household CF via the replacement of heating and cooling equipment as the air-conditioner by the more efficient one [55, 56]. Policymakers could deliver subsidies for replacement, require energy efficiency labelling in real estate listings, enforce high standards on new construction, and support energy efficiency retrofit programs. Additionally, it is also important to encourage consumers to save water heating e.g. through shorter showers and less frequent baths because its contribution to the home-related energy has been dominant; or to invest in more carbon efficient methods of providing hot water such as rooftop solar heaters [57]. A final recommendation is to reduce excessive consumption [30, 58]. We observed that cities in urban area especially Kanto area, including Tokyo and Yokohama, consume food and durable goods at rates much higher than the national average. Without directly intervening, policymakers still have opportunities to promote more sustainable consumption patterns. In terms of diets, policymakers could help to encourage a transition to a lower trophic level diet [59], encourage reducing alcohol, confectionary, and restaurant consumption [60],

work to decrease food waste, and encourage plant-based diets.

CF inventories of cities are fundamental information needed for guiding and evaluating policy. With accurate and detailed CF inventories it becomes possible to form more precise policy guidance and to undertake studies which identify the role of key factors and actions in affecting a city's CF. City policy makers can analyze their cities' characteristics from our analytical results in order to find suitable policies to help reduce their city's scope 3 footprint. The inventories offer by this study provide a data foundation which can guide this important work.

As we have shown, different cities have different CF compositions. Spatially detailed and city-level inventories can help policymakers at the national, province/prefecture/state, and county/municipality level to allocate resources and set priorities tailored to their jurisdiction. While the GHG implications of specific actions (e.g. replacing one car trip with a bike or train trip, or replacing one beef-based meal with a vegetarian one) are well documented in the literature, mapping the CF profile at broader spatial scales makes it possible to better target interventions (e.g. where to improve public transit, or where to advertise meatless Mondays.) City and prefecture level officials would not be able to set such priorities as effectively if they only had a list of individual intervention opportunities and no sense of which opportunities can be pursued where and at what scale.

Ideally detailed city and province-level PBA and CBA emissions inventories should be a product of either the national statistics or national environmental management agency. Such inventories are a fundamental requirement for guiding countries on a

maximally effective and minimally disruptive trajectory toward a zero-emissions society. In the absence of such official inventories provided by national agencies, unofficial inventories produced by the academic sector, such as the present offering, can serve as a placeholder until—hopefully—official data become available.

The model results are available at: <http://city.spatialfootprint.com/#japan>

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## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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