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Spatial Distribution of U.S. Household Carbon Footprints Reveals Suburbanization Undermines Greenhouse Gas Benefits of Urban Population Density

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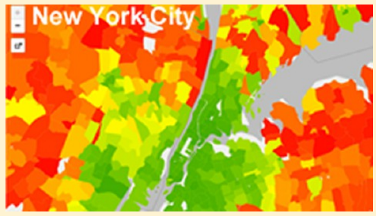
Supporting Information

ABSTRACT: Which municipalities and locations within the United States contribute the most to household greenhouse gas emissions, and what is the effect of population density and suburbanization on emissions? Using national household surveys, we developed econometric models of demand for energy, transportation, food, goods, and services that were used to derive average household carbon footprints (HCF) for U.S. zip codes, cities, counties, and metropolitan areas. We find consistently lower HCF in urban core cities (~40 tCO_2e) and higher carbon footprints in outlying suburbs (~50 tCO_2e), with a range from ~25 to >80 tCO_2e in the 50 largest metropolitan areas. Population density exhibits a weak but positive correlation with HCF until a density threshold is met, after which range, mean, and standard deviation of HCF decline. While population density contributes to relatively low HCF in the central cities of large metropolitan areas, the more extensive suburbanization in these regions contributes to an overall net increase in HCF compared to smaller metropolitan areas. Suburbs alone account for ~50% of total U.S. HCF. Differences in the size, composition, and location of household carbon footprints suggest the need for tailoring of greenhouse gas (GHG) mitigation efforts to different populations.



■ BACKGROUND

Demand for energy, transportation, food, goods and services drives global anthropogenic emissions of greenhouse gases (GHGs). Households in the United States alone are directly or indirectly responsible for about 20% of annual global GHG emissions,[1,2] yet represent only 4.3% of total global population. In the absence of comprehensive national climate policy, U.S. states and over 1000 U.S. mayors have committed to GHG reductions.[3] In response, a new protocol exists for managing community-scale GHG emissions that emphasizes contributions from households.[4] For compliance and voluntary policies to be effective, information is needed on the size and composition of household carbon footprints for all regions, at metropolitan, county, city, and even neighborhood scales. As global urbanization accelerates, increasing by 2.7 billion people by 2050,[5] the lessons from the data-rich U.S. experience may have increasing importance for planning efforts in urban areas of the world's expanding list of mega-cities.

Previous research using a diverse set of methods focused largely on large metropolitan regions or cities has shown that household carbon footprints (HCF) vary considerably, with energy, transportation, or consumption comprising a larger share of the total and with households in some locations contributing far more emissions than others.[6−9] For example, motor vehicles in California comprises 30% of HCF, compared to 6% for household electricity, while electricity is frequently the largest single source of emissions in locations with predominantly coal-fired electricity.[10] Income, household size, and social factors have been shown to affect total HCF, while a large number of factors have been shown to contribute to household energy and transportation-related emissions.[1,8,11,12]

A number of studies suggest that geographic differences in emissions are in part explained by population density. Population-dense municipalities tend to be urban centers with employment, housing, and services closely colocated, reducing travel distances, increasing demand for public transit, and with less space for larger homes. Early research by Newman and Kenworthy,[13] using data on 32 global cities, suggested a strong negative log−linear correlation between vehicle fuels and density (Figure S-1 in Supporting Information). More recent work using data from domestic and global cities has also seemed to confirm this relationship, although with more variance than previously thought.[14] One thread of research suggests that urban form (colocation of housing, employment and services) to be a more important factor.[15] Other studies suggest that neither density nor urban form result in large CO_2 benefits, and these may be outweighed by other social costs, such as crowding and higher rents.[16]

These earlier studies have been limited to analyzing a small set of case studies, and the resulting conclusions are difficult to generalize beyond those included in the studies themselves. A large, nationwide data set of all locations at fine geographic resolution holds potential to reassess the urban form hypothesis to more accurately describe the relationship between

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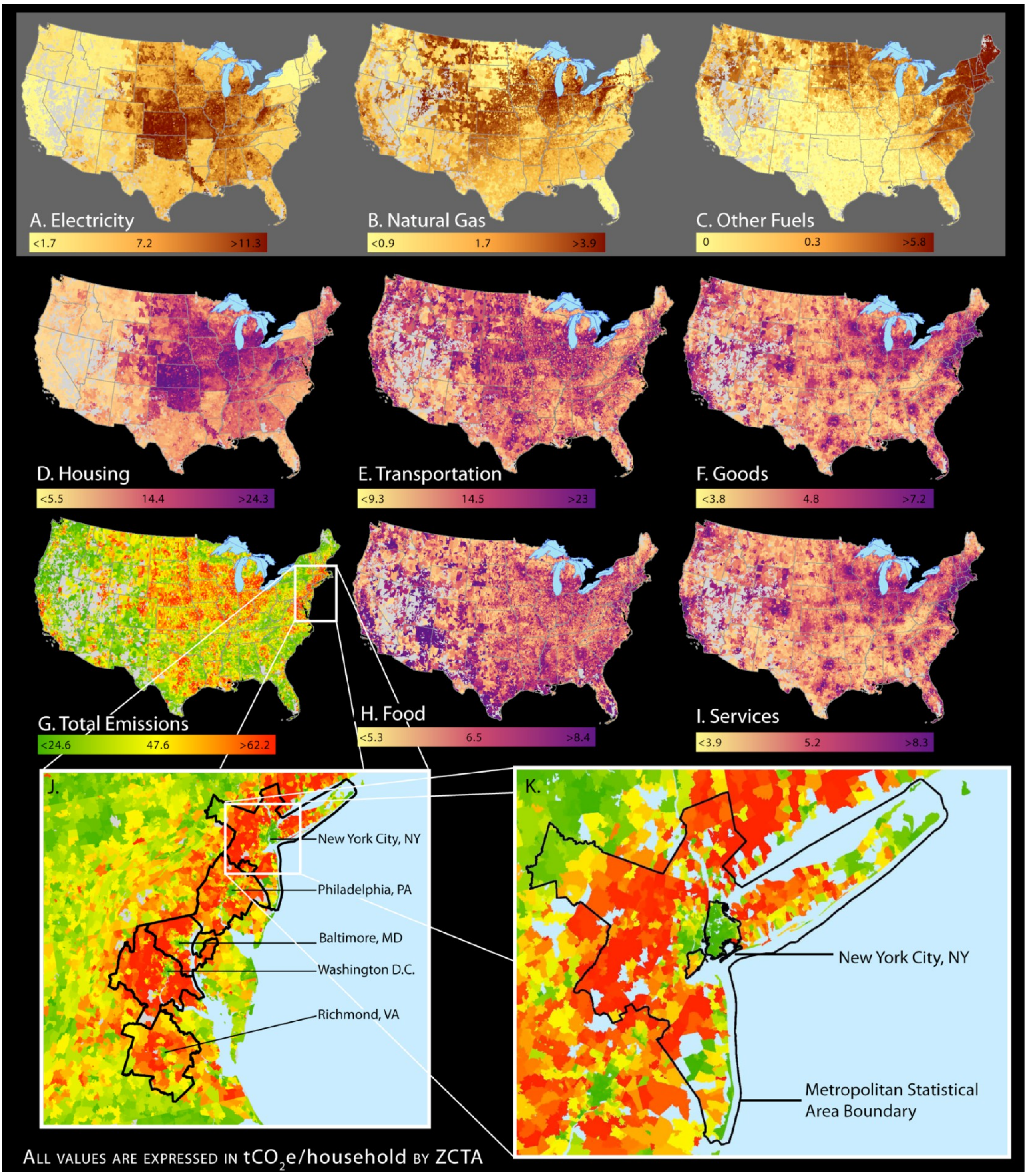

Figure 1. HCF from (A) electricity, (B) natural gas, (C) fuel oil and other fuels, (D) housing = A + B + C + water, waste, and home construction, (E) transportation, (F) goods, (H) food, (I) services, and (G) total = D + E + F + H + I. Transportation includes motor vehicle fuel, lifecycle emissions from fuel, motor vehicle manufacturing, air travel direct and indirect emissions, and public transit. Scales below each map show gradients of 30 colors, with labels for upper value of lowest of quantile, median value and lowest value of highest quantile, in metric tons CO_2e per household, for zip code tabulation areas (ZCTAs). East Coast metropolitan statistical areas (J), with a larger map of New York metropolitan area (K, outer line) and New York City (K, inner line) highlight the consistent pattern of relatively low GHG urban core cities and high GHG suburbs.

population, policy, urban form, and emissions. Our primary research questions are (1) how much variability exists in the size and composition of household carbon footprints across all U.S. locations and (2) how much of this variability can be explained by population density, income, home size, or other factors contributing to carbon footprints in urban, suburban, and rural areas?

In this work, we developed econometric models to estimate household energy, transportation, consumption of goods and services, and total household carbon footprints at fine geographic resolution. Min et al.[17] used national energy surveys

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to develop econometric models that could be applied at zip code tabulation areas to reasonably estimate household energy consumption. Other work in the U.K. has used demographic and lifestyle data to estimate more comprehensive household carbon footprints at fine geographic resolution.[12,18]

We present a model that characterizes the size and composition of household carbon footprints for essentially every U.S. zip code, city, county, and U.S. state. Household carbon footprints are the greenhouse gas emissions required to produce distribute and dispose of all household consumption for one year, including emissions resulting from the purchase and use of motor vehicles, public transit, air travel, household energy, housing, food, water, consumer goods, and services. We use this information to develop high geospatial resolution household carbon profiles of each location and to analyze the effect of population density and level of urbanization on full life cycle GHG emissions.

METHODS AND MATERIALS

The total household carbon footprint, HCF, of any individual or population can be expressed simply as the product of consumption, C, in dollars or physical units, and emissions per unit of consumption, E, summed over each emissions activity (i) included in the model

$$\mathrm{HCF} = \sum C_i E_i \tag{1}$$

We use existing national household survey data to develop econometric models of demand, C in eq 1, for transportation, residential energy, food, goods, and services. Independent variables used to predict household electricity, natural gas and other household heating fuels in the Residential Energy Consumption Survey[19] (n = 4363) include energy prices, heating fuel type, heating and cooling degree days, structure of homes (number of rooms, percent single-detached, year home-built), demographic information (income, number of household members, age of householder, race), home ownership, percentage rural or urban, Census divisions, and U.S. state. Predictive variables for motor vehicles miles traveled (VMT) in the National Household Travel Survey[20] (n = 11 744) include number of vehicles owned, fuel prices, average time to work, percentage of commuters who drive to work, demographic information (income, number of household members, race), number of food and recreation establishments in the zip code, population density, Census region, and U.S. state. Independent variables for 13 categories of goods and 11 categories of services in the Consumer Expenditures Survey[21] (n = 6965) include household size and income. The total number of independent variables used in all models is 37, all of which were also compiled for zip codes for prediction purposes. Regression coefficients, t-statistics, and p-values for each independent variable, in addition to model summary statistics (adjusted r^2), various tests of model validation and description of uncertainty are provided in the Supporting Information.

The model regression coefficients were then applied to data known at the level of U.S. zip code tabulation areas (ZCTAs, or zip codes) to estimate demand for typical households of each category of consumption for >31k ZCTAs. Information on the demographic characteristics of population, the physical infrastructure of homes, travel patterns, and economic activity are from the U.S. Census.[22] Energy and fuel prices are from Energy Information Agency[23] at the level of U.S. states (EIA). Heating and cooling degree-days were interpolated for each zip code from 5500 NOAA weather stations[24] using Geographic Information Systems software. Diets for 15 categories of food for adults (first two household members) and children (remaining members) are from the USDA nutrition database.[25]

Demand was then multiplied by GHG emission factors, in carbon dioxide equivalents[26] for electricity,[27] fuels,[28] and upstream emissions from fuels.[29] Indirect life cycle emission factors for goods and services are from the CEDA economic input-output model.[30] Input−output life cycle assessment is widely used to approximate emissions from average goods per dollar of expenditures in the consumption literature.[31] Emissions from water, waste and home construction are from previous work[32] and assumed to be the same for all households due to lack of regionally specific data. We then created population weighted averages for each city, county, and U.S. state. Zip codes were further classified into urban core, urban, urban fringe, suburban, rural fringe, or rural to evaluate the effect of urban development on emissions using U.S. Census data.[33]

To be clear, the models do not measure consumption, but rather estimate demand for goods and services for average households in zip codes using econometric models of national household survey data. As such, the results should be considered benchmarks by which measurements may be compared. We are limited to only variables available for zip codes and have left out potentially important variables, such as fuel economy of vehicles and local energy policies. Local energy policies are reflected in the model only to a certain degree, by inclusion of some states as dummy variables.

The primary purpose of these models is prediction and not explanation or inference. Because of multicollinearity between independent variables, correlation coefficients should not be compared. To infer causation and explain the relative influence of independent variables, we conducted a separate analysis of results for which we do explore the influence of multicollinearity (see discussion of Table 3 in Results and Table S-7 in Supporting Information for a coefficient correlation matrix).

Herein, we present results highlighting regional differences and explore the impact of population density and suburbanization. The data set could also support a range of other potential results not included in this paper, including rankings, composition comparisons, mitigation analysis, efficiency ratings based on reported energy usage, quantitative spatial analysis, and comparison with source emissions. Interested readers are encouraged to visit the project Web site[34] to view detailed maps and results for any zip code, city, county, or U.S. state.

RESULTS

The broad regional patterns of household carbon footprints across the contiguous United States are shown in Figure 1 in aggregate, and for the home energy, transportation, goods, services, and food components. It is important to note that this map allocates all emissions to households at the point of residence (a consumption perspective), and not where emissions physically enter the atmosphere (a production perspective). All data are presented on a per household basis, but show similar spatial patterns when viewed on a per capita basis. The Midwest, noncoastal East, and much of the South have relatively high GHG emissions from electricity (1a), while the entire West and Northeast regions of the country show relatively low electricity emissions, due primarily to low carbon-intensity of electricity production. Natural gas (1b) and other heating fuels (1c) are concentrated in colder regions of the

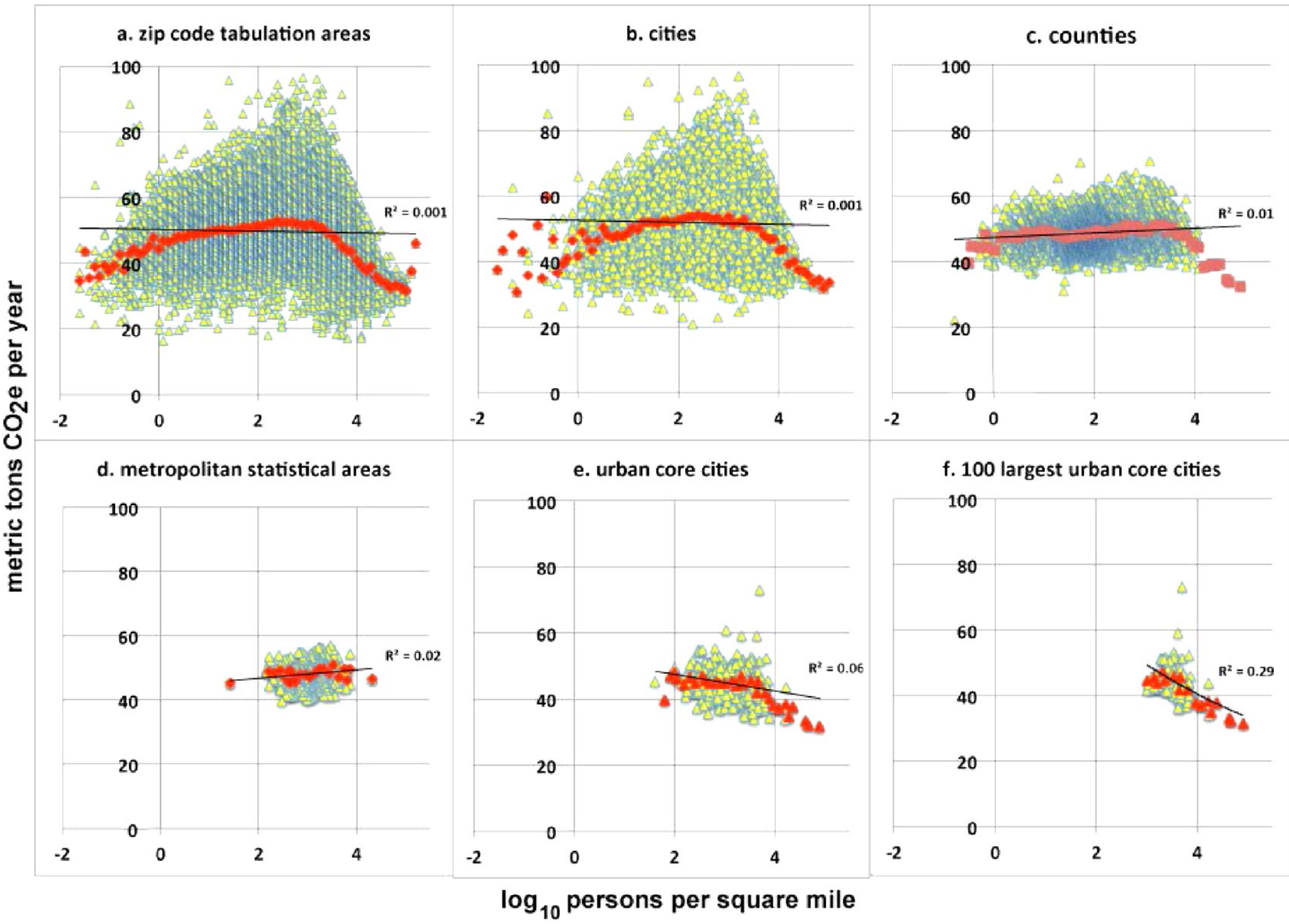


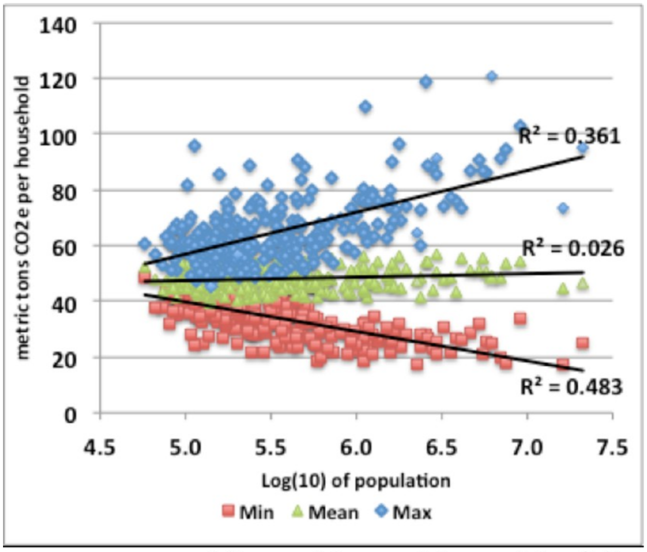
Figure 2. Average household carbon footprints (HCF) in (a) 31 531 zip code tabulation areas, (b) 10 093 U.S. Census cities and towns, (c) 3124 counties, (d) 276 metropolitan statistical areas, (e) 376 urban core cities, and (f) 100 largest urban core cities, by $\log_{10}$ of population per square mile (log of population density). The red line in each figure is the mean of all HCF for that population density, binned at increments of 0.1 on the *x*-axis. Linear goodness of fit trend lines show no correlation between population density and HCF, with the exception of the 100 largest urban core cities, R^2 = 0.29. Mean HCF decreases only after ~3000 persons per square mile (or 3.5 on the *x* axis).

country, including the Midwest, Northeast and parts of the Pacific. Combining all energy emissions along with the life cycle emissions of fuels, water, waste, and home construction into a single metric, "housing," (1d) presents a more comprehensive view of the contribution of homes to HCF than when considering energy components independently. Viewed through this lens, the Midwest and much of the South have relatively high emissions, so do parts of the Pacific and much of the Northeast. HCF from transportation (1e), goods (1f), food (1h), services (1i), and in total (1g) are widely distributed across the United States with no distinct broad regional patterns; however, the largest concentrations of HCF are surrounding metropolitan regions. When viewing HCF maps at regional spatial scales it is evident that GHG hotspots surrounding metropolitan regions have low carbon footprint cores, with rural areas exhibiting average to low carbon footprints. Figure 1j demonstrates this effect for East Coast metropolitan statistical areas. This pattern holds across the United States, with larger cities exhibiting the strongest urban/suburban differences, for example, the New York metropolitan statistical area (1k).

A number of factors account for differences between household carbon footprints in urban cores and suburbs. Supporting Information Figure S-2 shows transportation, energy, goods and total household carbon footprints for zip codes in the Atlanta metropolitan area. Atlanta was chosen as the example for this figure because it is the most populous landlocked MSA. All other large MSAs show very similar patterns. The zip codes with the highest energy-related emissions are concentrated in a tight band of suburbs between 15 and 45 miles from the city center. Despite having the same weather, energy prices and carbon-intensity of electricity production, suburbs still exhibit noticeably higher energy-related emissions. Geographic differences are most pronounced for transportation-related emissions, which range from <10 tCO_2e per household in the urban core to >25 tCO_2e in the most distant suburbs. Income and household size contribute to larger consumption-related carbon footprints in suburbs. The combined result is distinct carbon footprint rings surrounding urban cores, with suburbs exhibiting noticeably higher HCF.

This large data set allows for a more complete understanding of the effect of population density on communities than previous work limited to a number of cities. In Figure 2, total household carbon footprints are plotted against $\log_{10}$ of population density for all zip codes (a), cities (b), counties (c), metropolitan statistical areas (d), urban core cities (e) and the 100 most populous urban core cities (f). Carbon footprints in 10 093 cities (and also zip codes) are widely dispersed, with standard deviation of 9.2 and mean 52.0 tCO_2e. In contrast, carbon footprints of entire metropolitan statistical areas are quite similar, 48 tCO_2, SD 3.8. The red line in each figure is the mean of all HCF for that population density, binned at increments of 0.1 on the *x*-axis. Mean HCF, standard deviation and range increase moderately until a threshold of about 3,000 persons per square mile is reached (3.5 on the *x*-axis), after which mean HCF decreases logarithmically by about 10 tCO_2e for each 10-fold increase in population density. Linear trend lines plotted for each chart reveal virtually no correlation between population density and household carbon footprints (r^2 = 0.001 for zip codes and cities, 0.01 for counties and 0.02 for metropolitan areas), with the exception of the 100 largest cities (r^2 = 0.29). Other possible trend lines produce similar results, with or without a log *x*-axis. If plotting only the mean carbon footprints of highly dense cities, it is possible to find strong correlations between population density and transportation emissions or total HCF; however, this correlation almost completely disappears when considering all cities or metropolitan regions.

In agreement with population density hypotheses, large, dense metropolitan areas do contain locations in city cores with very low HCF compared to smaller, less dense cities, but they also contain suburbs with relatively high HCF, more than offsetting the benefit of low carbon areas in city centers. Figure 3 shows the min, mean, and max household carbon footprints of zip codes within each metropolitan statistical area (Supporting Information Figure S-4 is the same plot with population density on the *x*-axis instead of population). There is a strong negative correlation between population and min values (r^2 = 0.483) but also a strong positive correlation between population and max values (r^2 = 0.361). As metropolitan size increases the range between the lowest and highest HCF locations also increases, growing from a factor of 1.5 difference in small metropolitan areas to a factor of 4 difference in the largest. While the 25 most populous MSAs contain locations with 50% lower HCF than average, there is a small but noticeable trend of higher overall household carbon footprints in larger metropolitan areas because of the influence of outlying suburbs. The two largest metropolises, New York and Los Angeles, break this trend by demonstrating lower than average HCF.



	Min	Mean	Max	Max/Min
10 smallest	40.3	46.7	58.8	1.5
50 smallest	41.5	47.9	61.4	1.5
100 smallest	39.8	47.7	59.7	1.5
All MSAs	34.1	48.1	65.0	1.9
100 largest	27.8	48.6	72.5	2.6
50 largest	26.1	49.5	79.9	3.1
25 largest	25.2	50.1	85.5	3.4
10 largest	24.6	50.6	92.9	3.8

Figure 3. Min, mean and max carbon footprints of zip codes within 276 metropolitan statistical areas (*y*-axis) by $\log_{10}$ of total population (*x*-axis).

Analysis of all urban cores (also called principal cities), suburbs, and rural areas is presented in Tables 1 and 2. Large, population-dense cities, which are defined as urbanized areas inside a principal city,[33] have lower HCF than smaller principal cities; however, the opposite is true with large, relatively population dense suburbs, which have higher HCF than smaller suburbs (Table 1). We find no evidence that increased population density correlates directly with lower household

Table 1. Summary of Household Carbon Footprints (HCF) of Urban Core Cities, Suburban Cities, Suburban Towns, and Rural Areas for Sample of Zip Codes Categorized by NCHS[33a]

	trans	total	st. dev.	pop. (M)	pop. density
city, large	11.3	41.8	8.2	20.3	9953
city, midsize	13.9	45.1	9.5	7.3	3583
city, small	14.6	46.6	7.3	13.4	2117
rural, remote	16.0	47.6	5.6	4.4	15
town, distant territory	16.1	48.7	5.1	15.0	160
suburb, small territory	16.8	50.0	6.1	3.3	494
suburb, midsize	17.3	51.0	7.0	5.0	902
rural, distant	18.0	51.3	6.1	9.0	74
suburb, large	16.9	53.1	8.9	43.9	2706
town, fringe	18.2	53.2	14.7	3.8	251
town, remote territory	18.4	54.5	18.8	1.3	93
rural, fringe	19.1	55.8	7.8	12.9	254

[a]See Supporting Materials for definitions of location types. Table includes HCF for transportation, total HCF, standard deviation of total HCF, total population in the sample (in millions of residents), and population density (persons per square mile).

Table 2. Household Carbon Footprints in Metropolitan Statistical Area Principal Cities, Suburbs, and Rural and Micropolitan Areas (MSAs)[a]

	pop. (M)	tCO2/cap	tCO2/hh	MtCO2	percentage
metropolitan areas	241	18.4	49	4442	80%
principal cities	98	17.2	44	1695	30%
suburban	143	19.3	53	2747	49%
rural and micropolitan	59	19.5	50	1145	20%
total	300	18.6	49	5588	100%

[a]Table includes almost all populated zip codes in the U.S. and per capital and per household HCF for model year 2007. All locations not in principal cities, as classified by Census, but within metropolitan statistical areas are considered "suburbs".

carbon footprints in suburbs or rural areas; in fact, the opposite appears to be true. Transportation carbon footprints are about 50% higher in large suburbs compared to large principal cities, while total carbon footprints are about 25% higher, or 10 tCO_2e.

Table 2 summarizes results from all U.S. zip codes, including 300 M people, or over 99.6% of total U.S. population in the model year of 2007. Metropolitan statistical areas account for about 80% of the U.S. population and household carbon footprints. Principal cities, as defined by the U.S. Census, account for about 30% of U.S. carbon footprints, while locations outside of principal cities but still within metropolitan areas (suburbs), account for about 50% of total U.S. household contributions to climate change.

Total HCF for all U.S. locations is nearly 6 billion metric tons of CO_2 equivalent, or about 80% of total U.S. GHG emissions, but would likely be equivalent to nearly 100% of total U.S. GHG emissions if the carbon intensity of imports were considered.[1] Our estimate aligns very closely with other national HCF studies of the United States,[1,10,35] all of which estimate average U.S. HCF at about 50 tCO_2e. Future versions of this work would benefit from inclusion of a multiregional input-output model to account for the carbon intensity of international supply chains.[1,36]

To develop the best explanatory model of the results we regressed total HCF against all independent variables used in our econometric models (vehicle ownership, household size, energy prices, etc.) for each zip code in the data set. Of the 37 independent variables included in the regression models, 6 variables explain 92.5% of the variability for all zip codes, 96.2% in principal core cities and 94.6% in suburbs, as measured by adjusted r^2. In order of their influence on HCF, controlling for all variables entered previously (or stepwise) these are: number of vehicles per household, annual household income, carbon intensity of electricity, number of rooms (a proxy for home size, which is not available for zip codes), natural log of persons in household and log of population density (model 1 in Table 3). The next most significant variables (not shown) are average time to work, fuel prices for gasoline and natural gas, heating degree days and average year homes built; inclusion of these variables improves adjusted r^2 from 0.925 to 0.935.

Overall, income is the single largest contributing factor to household carbon footprints (controlling for all other variables), but the combined effect of other model variables, controlling for income, has far greater influence on the model goodness of fit. Income is positively correlated with population density for all locations (R^2 = 0.339), but slightly negatively correlated when considering just principal cities (R^2 = 0.078).

Models 2−4 in Table 3 emphasize the role of population density on household carbon footprints. Consistent with Figure 3, model 2 confirms there is virtually no direct correlation between population density and HCF for all zip codes (β = 0.037, R^2 = 0.001) yet there is a reasonably strong correlation when considering only principal cities (β = 0.484, R^2 = 0.234). Population density also becomes strongly significant when controlling for income and household size (β = −0.3) for all locations (model 3). When controlling for rooms and number of vehicles, population density is no longer significant due to multicollinearity between population density and these variables (see Supporting Information for a correlation matrix). Thus, population density appears to affect the size of homes and vehicle ownership and these variables in turn affect HCF, along with income, the carbon intensity of electricity, household size, and other factors to a lesser degree.

Table 3. Summary Statistics for All Zip Codes in the Data Set (All), Principal Cities (Cores), and Suburbs[a]

		all	cores	suburbs
1	no. vehicles	0.338	0.183	0.310
	annual hh income	0.499	0.476	0.500
	g CO_2/kWh	0.271	0.255	0.288
	no. rooms	0.202	0.242	0.221
	ln persons per hh	0.179	0.255	0.154
	log pop. density	−0.126	−0.084	−0.123
	adj. R^2	*0.925*	*0.962*	*0 946*
2	2 log pop. density	0.037	−0.484	−0.076
	adj. R^2	*0.001*	*0.234*	*0 006*
3	annual hh income	0.754	0.683	0.780
	ln persons per hh	0.314	0.371	0.266
	log pop. density	−0.302	−0.320	−0.301
	year home built	−0.116	−0.060	−0.022
	adj. R^2	*0.653*	*0.812*	*0 691*
4	no. rooms	0.448	0.486	0.526
	no. vehicles	0.515	0.472	0.471
	ln persons per hh	0.008	−0.015*	−0.014**
	adj. R^2	*0.747*	*0 808*	*0 788*
	N	**31447**	**3646**	**11011**

[a]Standardized beta coefficients. $p < 0.001$ for all variables, except $*p < 0.1$, $**p < .01$. VIF < 2.1 for all variables.

The diverse composition of household carbon footprints between locations (see Supporting Information Figure S-3) is also of significance. Emissions from travel are 3 times larger than energy in some locations, while in other locations energy-related emissions are considerably higher than travel. Household energy comprises between 15% and 33% of total household carbon footprints for about 90% of locations, while transportation comprises between 26% and 42%. The carbon footprint of food ranges from 12% to 20% of total HCF and is in some cases larger than either transportation or energy carbon footprints. Previous research[9] has further shown that the size and composition of carbon footprints varies even more noticeably for households of different demographic characteristics within locations.

These results should be understood in the context of uncertainty and the methods used to derive the estimates. We have used national survey data to predict consumption at fine geographic scales and have used average GHG emission factors to estimate emissions. This approach hides important regional differences. For example, while we estimated vehicle miles traveled for every zip code in the U.S. using locally available data, we have assumed average vehicle fuel economy for all locations. We have also assumed similar diets, housing construction, water, and waste-related emissions because of a lack of regionally specific data. Some of the model variables may indicate multiple conflicting aspects of urban form. For example, increased travel time may simultaneously indicate increased traffic, higher use of public transit, and longer travel distances. Also, population density does not account for mixed use, such as commercial and industrial zones colocated in populated areas. Additionally, as noted under model validation in the Supporting Materials, the model tends to underestimate emissions for locations with relatively high consumption.

DISCUSSION

In this study, we characterize average household carbon footprints of essentially all populated U.S. locations and reveal a more nuanced relationship between population density and household carbon footprints. Previous research using much smaller data sets has suggested a negative correlation between population density and emissions; as population density increases, emissions decrease. In contrast, we find that the mean, standard deviation and range of emissions actually increase until a population density of about 3000 persons per square mile is reached, after which mean HCF declines logarithmically, leveling out at a lower limit of about 30 tCO_2 per household (35% below average) at densities over 50 000 persons per square mile. The net effect of this inverted-U relationship is no overall correlation between population density and HCF when considering all U.S. zip codes (r^2 <0.001, Figure 2a) and cities (r^2 <0.001, Figure 2b); however there is a strong negative log−linear correlation between population density and HCF if only considering the most populous cities (r^2 = 0.3, Figure 2f), consistent with previous studies.

When considering entire metropolitan statistical areas the inverted-U relationship disappears and the correlation appears to be slightly positive (Figures 2d and 3 and Supporting Information Figure S-4), similar to the left side of the inverted-U relationship for zip codes and cities. More populous metropolitan areas tend to have somewhat higher net HCF due to the influence of more extensive suburbs, which are on average 25% higher than urban cores (Figure 3). The two largest metropolitan areas, New York and Los Angeles, are exceptions with somewhat lower net carbon footprints, suggesting the inverted-U relationship may hold for extremely population-dense metropolitan areas, or megacities. Similar comprehensive studies in other countries are needed to compare the effects of population density and suburbanization to see if lessons in the U.S. are transferable.

Higher emissions in suburbs, and at moderate population densities, are due to a number of factors. First, urbanized areas are wealthier than rural areas, with higher consumption and emissions; however, at population densities above a threshold of about 3000 persons per square mile, household carbon footprints tend to be lower, primarily, due to smaller homes, shorter driving distances, and also somewhat lower incomes.

As a policy measure to reduce GHG emissions, increasing population density appears to have severe limitations and unexpected trade-offs. In suburbs, we find more population-dense suburbs actually have noticeably higher HCF, largely because of income effects. Population density does correlate with lower HCF when controlling for income and household size; however, in practice population density measures may have little control over income of residents. Increasing rents would also likely further contribute to pressures to suburbanize the suburbs, leading to a possible net increase in emissions. As a policy measure for urban cores, any such strategy should consider the larger impact on surrounding areas, not just the residents of population dense communities themselves. The relationship is also log−linear, with a 10-fold increase in population density yielding only a 25% decrease in HCF. Generally, we find no evidence for net GHG benefits of population density in urban cores or suburbs when considering effects on entire metropolitan areas.

Given these limitations of urban planning our data suggests that an entirely new approach of highly tailored, community-scale carbon management is urgently needed. Regions with high energy-related emissions, such as the Midwest, the South, and parts of the Northeast, should focus more on reducing household energy consumption than regions with relatively clean sources of energy, such as California. However, if household energy were the sole focus of residential GHG mitigation programs, then between two-thirds and 85% of household carbon footprints would be left unaddressed in most locations; the full carbon footprint of households should be considered in community GHG inventories and management plans. Suburbs, which account for 50% of total U.S. HCF, tend to have high motor vehicle emissions, large homes, and high incomes. These locations are ideal candidates for a combination of energy efficient technologies, including whole home energy upgrades and solar photovoltaic systems combined with electric vehicles. Food tends to be a much larger share of emissions in urban cores, where transportation and energy emissions tend to be lower, and in rural areas, where household size tends to be higher and consumption relatively low.

Several recent studies for California[37,38] conclude that 80% GHG reductions are possible only with near technical potential efficiencies in transportation, buildings, industry, and agriculture. To the extent that these efficiencies are not met, highly tailored behavior-based programs must make up the difference to decrease demand for energy, transportation, goods, and services that drive emissions.

ASSOCIATED CONTENT

Supporting Information

Detailed methods for the carbon footprint model, including regression coefficients, *t*-values, and *p*-values for each independent variable, model summary statistics (r^2), various tests of model validation, and description of uncertainty. This material is available free of charge via the Internet at http://pubs.acs.org. Carbon footprints profiles of all U.S. zip codes, cities, counties and states are available on the project Web site, http://coolclimate.berkeley.edu/carboncalculator, and an interactive mapping Web site, http://coolclimate.berkeley.edu/maps.

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Notes

The authors declare no competing financial interest.

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