

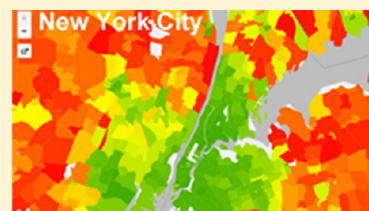
1 Spatial Distribution of U.S. Household Carbon Footprints Reveals 2 Suburbanization Undermines Greenhouse Gas Benefits of Urban 3 Population Density

4 Christopher Jones^{*,†} and Daniel M. Kammen^{*,†,‡,§}

5 [†]Energy and Resources Group, [‡]Goldman School of Public Policy, and [§]Department of Nuclear Engineering, University of California,
6 Berkeley, California 94720, United States

7 **S** Supporting Information

8 **ABSTRACT:** Which municipalities and locations within the United States contribute the
9 most to household greenhouse gas emissions, and what is the effect of population density
10 and suburbanization on emissions? Using national household surveys, we developed
11 econometric models of demand for energy, transportation, food, goods, and services that
12 were used to derive average household carbon footprints (HCF) for U.S. zip codes, cities,
13 counties, and metropolitan areas. We find consistently lower HCF in urban core cities
14 (~40 tCO₂e) and higher carbon footprints in outlying suburbs (~50 tCO₂e), with a range
15 from ~25 to >80 tCO₂e in the 50 largest metropolitan areas. Population density exhibits a
16 weak but positive correlation with HCF until a density threshold is met, after which range, mean, and standard deviation of HCF
17 decline. While population density contributes to relatively low HCF in the central cities of large metropolitan areas, the more
18 extensive suburbanization in these regions contributes to an overall net increase in HCF compared to smaller metropolitan areas.
19 Suburbs alone account for ~50% of total U.S. HCF. Differences in the size, composition, and location of household carbon
20 footprints suggest the need for tailoring of greenhouse gas (GHG) mitigation efforts to different populations.



21 ■ BACKGROUND

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

39 Previous research using a diverse set of methods focused
40 largely on large metropolitan regions or cities has shown that
41 household carbon footprints (HCF) vary considerably, with
42 energy, transportation, or consumption comprising a larger
43 share of the total and with households in some locations
44 contributing far more emissions than others.^{6–9} For example,
45 motor vehicles in California comprises 30% of HCF, compared
46 to 6% for household electricity, while electricity is frequently
47 the largest single source of emissions in locations with
48 predominantly coal-fired electricity.¹⁰ Income, household size,
49 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} 51

A number of studies suggest that geographic differences in
emissions are in part explained by population density. 52
Population-dense municipalities tend to be urban centers 53
with employment, housing, and services closely colocated, 54
reducing travel distances, increasing demand for public transit, 55
and with less space for larger homes. Early research by Newman 56
and Kenworthy,¹³ using data on 32 global cities, suggested a 57
strong negative log–linear correlation between vehicle fuels and 58
density (Figure S-1 in Supporting Information). More recent 60
work using data from domestic and global cities has also 61
seemed to confirm this relationship, although with more 62
variance than previously thought.¹⁴ One thread of research 63
suggests that urban form (collocation of housing, employment 64
and services) to be a more important factor.¹⁵ Other studies 65
suggest that neither density nor urban form result in large CO₂ 66
benefits, and these may be outweighed by other social costs, 67
such as crowding and higher rents.¹⁶ 68

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 74

Received: August 2, 2013

Revised: December 11, 2013

Accepted: December 13, 2013

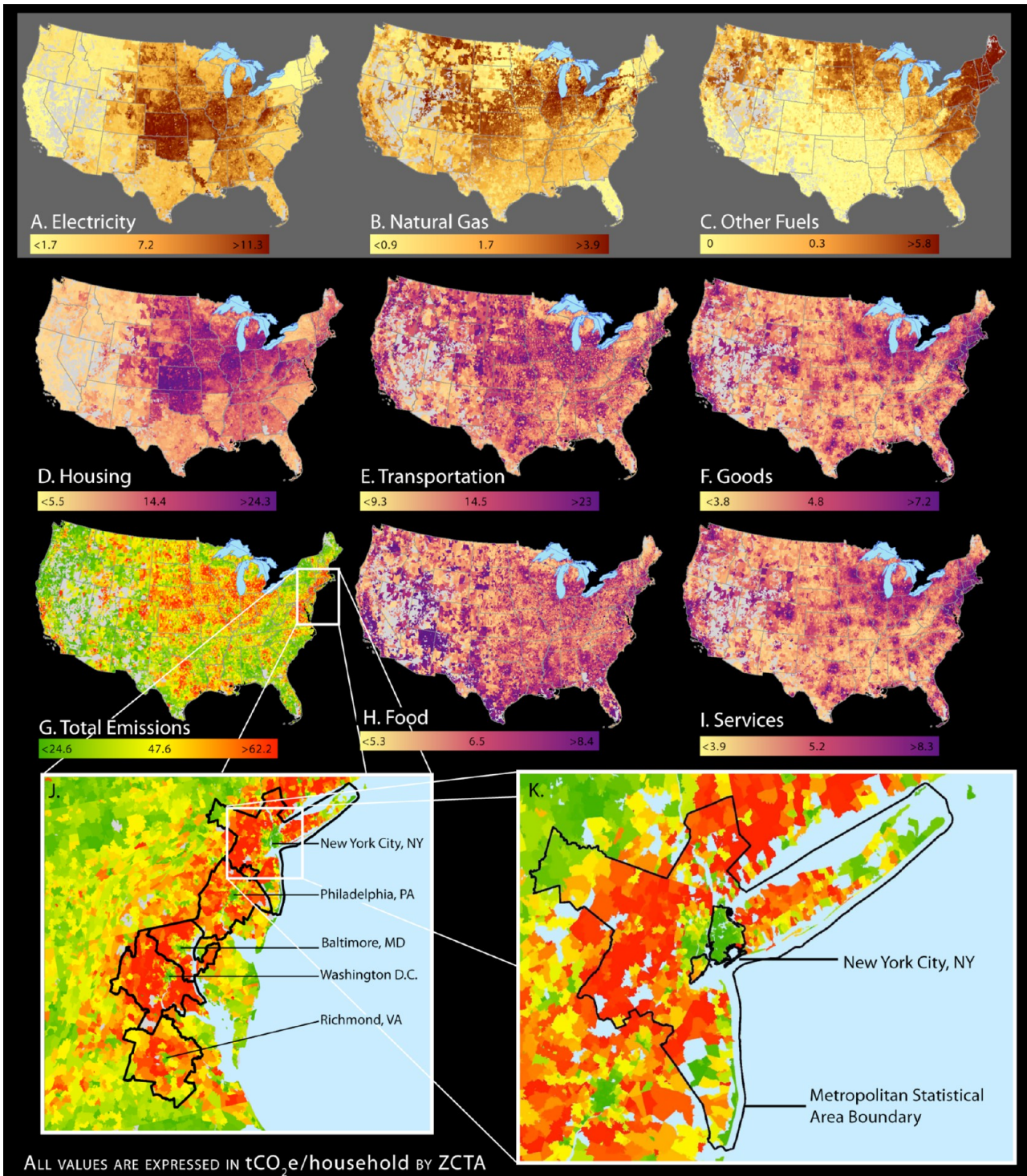


Figure 1. HCF from (A) electricity, (B) natural gas, (C) fuel oil and other fuels, (D) housing = A + B + C + water, waste, and home construction, (E) transportation, (F) goods, (H) food, (I) services, and (G) total = D + E + F + H + I. Transportation includes motor vehicle fuel, lifecycle emissions from 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 CO₂e 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.

75 population, policy, urban form, and emissions. Our primary
 76 research questions are (1) how much variability exists in the
 77 size and composition of household carbon footprints across all
 78 U.S. locations and (2) how much of this variability can be
 79 explained by population density, income, home size, or other

factors contributing to carbon footprints in urban, suburban, 80
 and rural areas? 81

In this work, we developed econometric models to estimate 82
 household energy, transportation, consumption of goods and 83
 services, and total household carbon footprints at fine 84
 geographic resolution. Min et al.¹⁷ used national energy surveys 85

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

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

103 ■ METHODS AND MATERIALS

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

$$109 \quad \text{HCF} = \sum C_i E_i \quad (1)$$

110 We use existing national household survey data to develop
111 econometric models of demand, C in eq 1, for transportation,
112 residential energy, food, goods, and services. Independent
113 variables used to predict household electricity, natural gas and
114 other household heating fuels in the Residential Energy
115 Consumption Survey¹⁹ ($n = 4363$) include energy prices,
116 heating fuel type, heating and cooling degree days, structure of
117 homes (number of rooms, percent single-detached, year home-
118 built), demographic information (income, number of house-
119 hold members, age of householder, race), home ownership,
120 percentage rural or urban, Census divisions, and U.S. state.
121 Predictive variables for motor vehicles miles traveled (VMT) in
122 the National Household Travel Survey²⁰ ($n = 11\,744$) include
123 number of vehicles owned, fuel prices, average time to work,
124 percentage of commuters who drive to work, demographic
125 information (income, number of household members, race),
126 number of food and recreation establishments in the zip code,
127 population density, Census region, and U.S. state. Independent
128 variables for 13 categories of goods and 11 categories of
129 services in the Consumer Expenditures Survey²¹ ($n = 6965$)
130 include household size and income. The total number of
131 independent variables used in all models is 37, all of which were
132 also compiled for zip codes for prediction purposes. Regression
133 coefficients, t -statistics, and p -values for each independent
134 variable, in addition to model summary statistics (adjusted r^2),
135 various tests of model validation and description of uncertainty
136 are provided in the Supporting Information.

137 The model regression coefficients were then applied to data
138 known at the level of U.S. zip code tabulation areas (ZCTAs, or
139 zip codes) to estimate demand for typical households of each
140 category of consumption for >31k ZCTAs. Information on the
141 demographic characteristics of population, the physical infra-
142 structure of homes, travel patterns, and economic activity are
143 from the U.S. Census.²² Energy and fuel prices are from Energy
144 Information Agency²³ at the level of U.S. states (EIA). Heating
145 and cooling degree-days were interpolated for each zip code

from 5500 NOAA weather stations²⁴ 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 equivalents²⁶ 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 work³² 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 multi-
collinearity (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 suburbaniza-
tion. 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 site³⁴ to view detailed maps
and results for any zip code, city, county, or U.S. state.

192 ■ 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 207

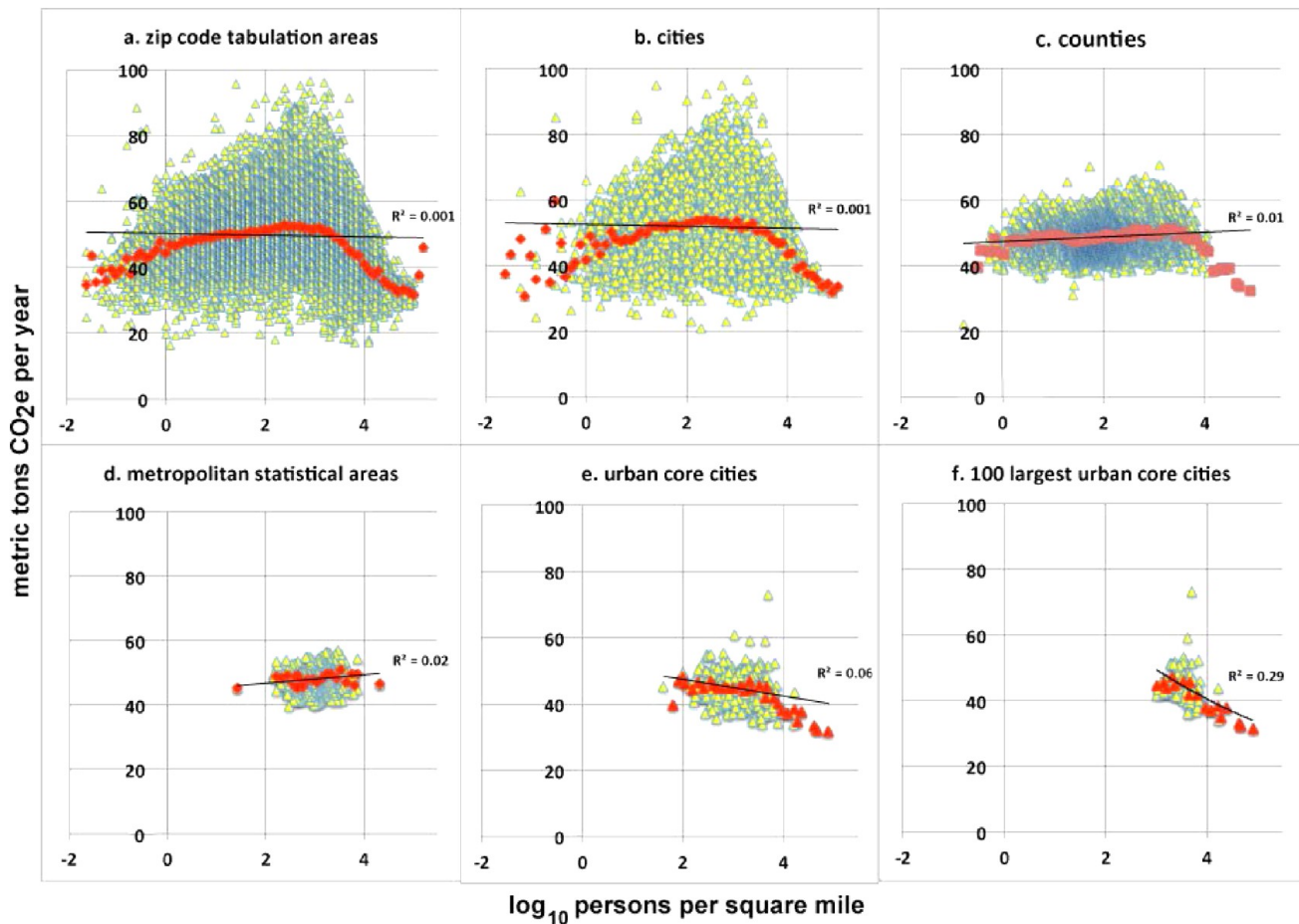


Figure 2. Average household carbon footprints (HCF) in (a) 31 531 zip code tabulation areas, (b) 10 093 U.S. Census cities and towns, (c) 3124 counties, (d) 276 metropolitan statistical areas, (e) 376 urban core cities, and (f) 100 largest urban core cities, by \log_{10} of population per square mile (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).

208 country, including the Midwest, Northeast and parts of the
 209 Pacific. Combining all energy emissions along with the life cycle
 210 emissions of fuels, water, waste, and home construction into a
 211 single metric, “housing,” (1d) presents a more comprehensive
 212 view of the contribution of homes to HCF than when
 213 considering energy components independently. Viewed
 214 through this lens, the Midwest and much of the South have
 215 relatively high emissions, so do parts of the Pacific and much of
 216 the Northeast. HCF from transportation (1e), goods (1f), food
 217 (1h), services (1i), and in total (1g) are widely distributed
 218 across the United States with no distinct broad regional
 219 patterns; however, the largest concentrations of HCF are
 220 surrounding metropolitan regions. When viewing HCF maps at
 221 regional spatial scales it is evident that GHG hotspots
 222 surrounding metropolitan regions have low carbon footprint
 223 cores, with rural areas exhibiting average to low carbon
 224 footprints. Figure 1j demonstrates this effect for East Coast
 225 metropolitan statistical areas. This pattern holds across the
 226 United States, with larger cities exhibiting the strongest urban/
 227 suburban differences, for example, the New York metropolitan
 228 statistical area (1k).

229 A number of factors account for differences between
 230 household carbon footprints in urban cores and suburbs.
 231 Supporting Information Figure S-2 shows transportation,
 232 energy, goods and total household carbon footprints for zip

codes in the Atlanta metropolitan area. Atlanta was chosen as
 233 the example for this figure because it is the most populous
 234 landlocked MSA. All other large MSAs show very similar
 235 patterns. The zip codes with the highest energy-related
 236 emissions are concentrated in a tight band of suburbs between
 237 15 and 45 miles from the city center. Despite having the same
 238 weather, energy prices and carbon-intensity of electricity
 239 production, suburbs still exhibit noticeably higher energy-
 240 related emissions. Geographic differences are most pronounced
 241 for transportation-related emissions, which range from <10
 242 tCO_2e per household in the urban core to >25 tCO_2e in the
 243 most distant suburbs. Income and household size contribute to
 244 larger consumption-related carbon footprints in suburbs. The
 245 combined result is distinct carbon footprint rings surrounding
 246 urban cores, with suburbs exhibiting noticeably higher HCF.
 247

This large data set allows for a more complete understanding
 248 of the effect of population density on communities than
 249 previous work limited to a number of cities. In Figure 2, total
 250 household carbon footprints are plotted against \log_{10} of
 251 population density for all zip codes (a), cities (b), counties
 252 (c), metropolitan statistical areas (d), urban core cities (e)
 253 and the 100 most populous urban core cities (f). Carbon footprints
 254 in 10 093 cities (and also zip codes) are widely dispersed, with
 255 standard deviation of 9.2 and mean 52.0 tCO_2e . In contrast,
 256 carbon footprints of entire metropolitan statistical areas are 257

quite similar, 48 tCO₂, 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 tCO₂e 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

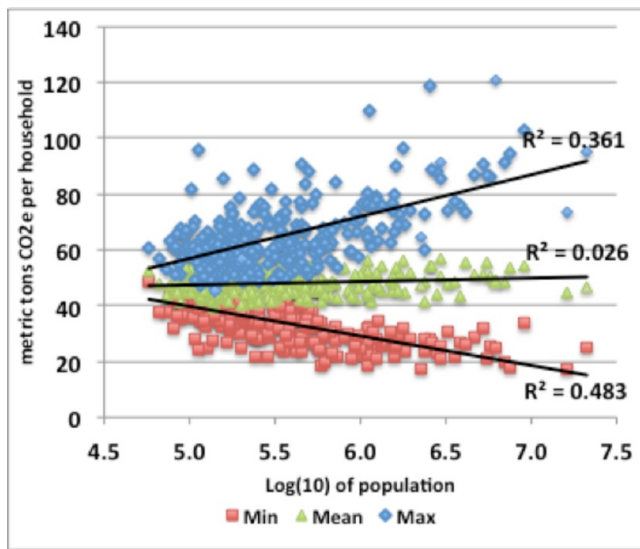
population density on the *x*-axis instead of population). There is a strong negative correlation between population and min values ($r^2 = 0.483$) but also a strong positive correlation between population and max values ($r^2 = 0.361$). As metropolitan size increases the range between the lowest and 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.

Analysis of all urban cores (also called principal cities), suburbs, and rural areas is presented in Tables 1 and 2. Large, rural areas is presented in Tables 1 and 2. Large,

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

^aSee 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).



	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 log₁₀ of total population (*x*-axis).

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

	pop. (M)	tCO ₂ /cap	tCO ₂ /hh	MtCO ₂	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%

^aTable includes almost all populated zip codes in the U.S. and per capita 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”.

306 carbon footprints in suburbs or rural areas; in fact, the opposite
 307 appears to be true. Transportation carbon footprints are about
 308 50% higher in large suburbs compared to large principal cities,
 309 while total carbon footprints are about 25% higher, or 10
 310 tCO₂e.

311 Table 2 summarizes results from all U.S. zip codes, including
 312 300 M people, or over 99.6% of total U.S. population in the
 313 model year of 2007. Metropolitan statistical areas account for
 314 about 80% of the U.S. population and household carbon
 315 footprints. Principal cities, as defined by the U.S. Census,
 316 account for about 30% of U.S. carbon footprints, while
 317 locations outside of principal cities but still within metropolitan
 318 areas (suburbs), account for about 50% of total U.S. household
 319 contributions to climate change.

320 Total HCF for all U.S. locations is nearly 6 billion metric
 321 tons of CO₂ equivalent, or about 80% of total U.S. GHG
 322 emissions, but would likely be equivalent to nearly 100% of
 323 total U.S. GHG emissions if the carbon intensity of imports
 324 were considered.¹ Our estimate aligns very closely with other
 325 national HCF studies of the United States,^{1,10,35} all of which
 326 estimate average U.S. HCF at about 50 tCO₂e. Future versions
 327 of this work would benefit from inclusion of a multiregional
 328 input-output model to account for the carbon intensity of
 329 international supply chains.^{1,36}

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

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

354 Models 2–4 in Table 3 emphasize the role of population
 355 density on household carbon footprints. Consistent with Figure
 356 3, model 2 confirms there is virtually no direct correlation
 357 between population density and HCF for all zip codes (*β* =
 358 0.037, *R*² = 0.001) yet there is a reasonably strong correlation
 359 when considering only principal cities (*β* = 0.484, *R*² = 0.234).
 360 Population density also becomes strongly significant when
 361 controlling for income and household size (*β* = −0.3) for all
 362 locations (model 3). When controlling for rooms and number
 363 of vehicles, population density is no longer significant due to
 364 multicollinearity between population density and these
 365 variables (see Supporting Information for a correlation matrix).
 366 Thus, population density appears to affect the size of homes
 367 and vehicle ownership and these variables in turn affect HCF,

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. <i>R</i> ²	0.925	0.962	0.946
2	2 log pop. density	0.037	−0.484	−0.076
	adj. <i>R</i> 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. <i>R</i> 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. <i>R</i> ²	0.747	0.808	0.788
	N	31447	3646	11011

^aStandardized beta coefficients. *p* < 0.001 for all variables, except **p* < 0.1, ***p* < .01. VIF < 2.1 for all variables.

368 along with income, the carbon intensity of electricity,
 369 household size, and other factors to a lesser degree.

370 The diverse composition of household carbon footprints
 371 between locations (see Supporting Information Figure S-3) is
 372 also of significance. Emissions from travel are 3 times larger
 373 than energy in some locations, while in other locations energy-
 374 related emissions are considerably higher than travel. House-
 375 hold energy comprises between 15% and 33% of total
 376 household carbon footprints for about 90% of locations,
 377 while transportation comprises between 26% and 42%. The
 378 carbon footprint of food ranges from 12% to 20% of total HCF
 379 and is in some cases larger than either transportation or energy
 380 carbon footprints. Previous research⁹ has further shown that the
 381 size and composition of carbon footprints varies even more
 382 noticeably for households of different demographic character-
 383 istics within locations.

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

403 ■ DISCUSSION

404 In this study, we characterize average household carbon
 405 footprints of essentially all populated U.S. locations and reveal
 406 a more nuanced relationship between population density and
 407 household carbon footprints. Previous research using much
 408 smaller data sets has suggested a negative correlation between
 409 population density and emissions; as population density
 410 increases, emissions decrease. In contrast, we find that the
 411 mean, standard deviation and range of emissions actually
 412 increase until a population density of about 3000 persons per
 413 square mile is reached, after which mean HCF declines
 414 logarithmically, leveling out at a lower limit of about 30 tCO₂
 415 per household (35% below average) at densities over 50 000
 416 persons per square mile. The net effect of this inverted-U
 417 relationship is no overall correlation between population
 418 density and HCF when considering all U.S. zip codes (r^2
 419 <0.001, Figure 2a) and cities (r^2 <0.001, Figure 2b); however
 420 there is a strong negative log-linear correlation between
 421 population density and HCF if only considering the most
 422 populous cities (r^2 = 0.3, Figure 2f), consistent with previous
 423 studies.

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

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

446 As a policy measure to reduce GHG emissions, increasing
 447 population density appears to have severe limitations and
 448 unexpected trade-offs. In suburbs, we find more population-
 449 dense suburbs actually have noticeably higher HCF, largely
 450 because of income effects. Population density does correlate
 451 with lower HCF when controlling for income and household
 452 size; however, in practice population density measures may
 453 have little control over income of residents. Increasing rents
 454 would also likely further contribute to pressures to suburbanize
 455 the suburbs, leading to a possible net increase in emissions. As a
 456 policy measure for urban cores, any such strategy should
 457 consider the larger impact on surrounding areas, not just the
 458 residents of population dense communities themselves. The
 459 relationship is also log-linear, with a 10-fold increase in
 460 population density yielding only a 25% decrease in HCF.
 461 Generally, we find no evidence for net GHG benefits of
 462 population density in urban cores or suburbs when considering
 463 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 agricul-
 ture. 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://](http://pubs.acs.org)
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 inter-
 active mapping Web site, [http://coolclimate.berkeley.edu/](http://coolclimate.berkeley.edu/maps)
[maps](http://coolclimate.berkeley.edu/maps).

■ AUTHOR INFORMATION

Corresponding Authors

*Phone: (510) 643-5048. E-mail: cmjones@berkeley.edu.

*Address: Renewable and Appropriate Energy Laboratory,
 University of California, Berkeley, CA 94720-3050. Phone:
 (510) 642-1139. Fax: (510) 642-1085. E-mail: [kammen@](mailto:kammen@berkeley.edu)
[berkeley.edu](mailto:kammen@berkeley.edu).

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

The authors would like to thank the California Air Resources
 Board for financial support (contracts 07-344 and 09-359), UC
 Berkeley graduate students Joe Kantenbacher and Kate
 Foreman for research assistance, and Kamini Iyer for
 production of the GIS maps used in this paper. This work
 was supported by NSF grant SMA-1338539 to DMK. We also
 thank the Karsten Family Foundation for support of the
 Renewable and Appropriate Energy Laboratory and the Class
 of 1935 of the University of California, Berkeley.

523 ■ REFERENCES

- 524 (1) Weber, C. L.; Matthews, H. S. Quantifying the Global and
525 Distributional Aspects of American Household Carbon Footprint. *Ecol.*
526 *Econ.* **2008**, *66*, 379–391.
- 527 (2) Hertwich, E. G.; Peters, G. P. Carbon Footprint of Nations: A
528 Global, Trade-Linked Analysis. *Environ. Sci. Technol.* **2009**, *43*, 6414–
529 6420.
- 530 (3) The Agreement—Mayors Climate Protection Center. [http://](http://www.usmayors.org/climateprotection/agreement.htm)
531 www.usmayors.org/climateprotection/agreement.htm (accessed Jul
532 31, 2013).
- 533 (4) U.S. Community Protocol for Accounting and Reporting of
534 Greenhouse Gas Emissions—ICLEI Local Governments for Sustain-
535 ability U.S.A. [http://www.iclei.usa.org/tools/ghg-protocol/](http://www.iclei.usa.org/tools/ghg-protocol/community-protocol/us-community-protocol-for-accounting-and-reporting-of-greenhouse-gas-emissions)
536 [community-protocol/us-community-protocol-for-accounting-and-](http://www.iclei.usa.org/tools/ghg-protocol/community-protocol/us-community-protocol-for-accounting-and-reporting-of-greenhouse-gas-emissions)
537 [reporting-of-greenhouse-gas-emissions](http://www.iclei.usa.org/tools/ghg-protocol/community-protocol/us-community-protocol-for-accounting-and-reporting-of-greenhouse-gas-emissions) (accessed Jul 31, 2013).
- 538 (5) United Nations. *World Urbanization Prospects: The 2011 Revision*;
539 United Nations, Population Division: New York, 2011.
- 540 (6) Hillman, T.; Ramaswami, A. Greenhouse Gas Emission
541 Footprints and Energy Use Benchmarks for Eight U.S. Cities. *Environ.*
542 *Sci. Technol.* **2010**, *44*, 1902–1910.
- 543 (7) Sovacool, B. K.; Brown, M. A. Twelve Metropolitan Carbon
544 Footprints: A Preliminary Comparative Global Assessment. *Energy*
545 *Policy* **2010**, *38*, 4856–4869.
- 546 (8) Glaeser, E. L.; Kahn, M. E. The Greenness of Cities: Carbon
547 Dioxide Emissions and Urban Development. *J. Urban Econ.* **2010**, *67*,
548 404–418.
- 549 (9) Wiedenhofer, D.; Lenzen, M.; Steinberger, J. K. Energy
550 Requirements of Consumption: Urban Form, Climatic and Socio-
551 Economic Factors, Rebounds and Their Policy Implications. *Energy*
552 *Policy* **2013**, *63*, 696–707.
- 553 (10) Jones, C. M.; Kammen, D. M. Quantifying Carbon Footprint
554 Reduction Opportunities for U.S. Households and Communities.
555 *Environ. Sci. Technol.* **2011**, *45*, 4088–4095.
- 556 (11) Lenzen, M.; Wier, M.; Cohen, C.; Hayami, H.; Pachauri, S.;
557 Schaeffer, R. A Comparative Multivariate Analysis of Household
558 Energy Requirements in Australia, Brazil, Denmark, India and Japan.
559 *Energy* **2006**, *31*, 181–207.
- 560 (12) Baiocchi, G.; Minx, J.; Hubacek, K. The Impact of Social Factors
561 and Consumer Behavior on Carbon Dioxide Emissions in the United
562 Kingdom. *J. Ind. Ecol.* **2010**, *14*, 50–72.
- 563 (13) Newman, P. W. G.; Kenworthy, J. R. Gasoline Consumption
564 and Cities. *J. Am. Plann. Assoc.* **1989**, *55*, 24–37.
- 565 (14) Karathodorou, N.; Graham, D. J.; Noland, R. B. Estimating the
566 Effect of Urban Density on Fuel Demand. *Energy Econ.* **2010**, *32*, 86–
567 92.
- 568 (15) Ewing, R.; Cervero, R. Travel and the Built Environment: A
569 Synthesis. *Transp. Res. Rec. J. Transp. Res. Board* **2001**, *1780*, 87–114.
- 570 (16) Echenique, M. H.; Hargreaves, A. J.; Mitchell, G.; Namdeo, A.
571 Growing Cities Sustainably. *J. Am. Plann. Assoc.* **2012**, *78*, 121–137.
- 572 (17) Min, J.; Hausfather, Z.; Lin, Q. F. A High-Resolution Statistical
573 Model of Residential Energy End Use Characteristics for the United
574 States. *J. Ind. Ecol.* **2010**, *14*, 791–807.
- 575 (18) Minx, J.; Baiocchi, G.; Wiedmann, T.; Barrett, J.; Creutzig, F.;
576 Feng, K.; Förster, M.; Pichler, P.-P.; Weisz, H.; Hubacek, K. Carbon
577 Footprints of Cities and Other Human Settlements in the UK. *Environ.*
578 *Res. Lett.* **2013**, *8*, 035039.
- 579 (19) U.S. Energy Information Administration. Residential Energy
580 Consumption Survey, 2003.
- 581 (20) Highlights of the 2001 National Household Travel Survey.
582 [http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/](http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/highlights_of_the_2001_national_household_travel_survey/index.html)
583 [highlights_of_the_2001_national_household_travel_survey/index.](http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/highlights_of_the_2001_national_household_travel_survey/index.html)
584 [html](http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/highlights_of_the_2001_national_household_travel_survey/index.html) (accessed Jul 9, 2013).
- 585 (21) Bureau of Labor Statistics. Consumer Expenditures Survey,
586 2008.
- 587 (22) Bureau, U. S. C. American FactFinder. [http://factfinder2.census.](http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml)
588 [gov/faces/nav/jsf/pages/index.xhtml](http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml) (accessed Aug 1, 2013).
- 589 (23) U.S. Energy Information Administration (EIA). [http://www.eia.](http://www.eia.gov/)
590 [gov/](http://www.eia.gov/) (accessed Aug 1, 2013).
- (24) National Oceanic and Atmospheric Administration. *Monthly*
591 *Normals of Temperature, Precipitation, and Heating and Cooling Degree*
592 *Days 1971–2000*; Climatography of the United States No. 81;
593 National Oceanic and Atmospheric Administration: Washington, DC,
594 2002. 595
- (25) NDL/FNIC. Food Composition Database Home Page. [http://](http://ndb.nal.usda.gov/)
596 ndb.nal.usda.gov/ (accessed Aug 1, 2013). 597
- (26) Solomon, S. *Climate Change 2007—The Physical Science Basis: The*
598 *Working Group I Contribution to the Fourth Assessment Report of the*
599 *IPCC*; Cambridge University Press: Cambridge, U.K., 2007. 600
- (27) eGRID. [http://www.epa.gov/cleanenergy/energy-resources/](http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html)
601 [egrid/index.html](http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html) (accessed Aug 1, 2013). 602
- (28) Office of Air Quality Planning and Standards, U. E. Emissions
603 Factors & AP 42 <http://www.epa.gov/ttnchie1/ap42/> (accessed Aug
604 1, 2013). 605
- (29) Argonne GREET Model. <http://greet.es.anl.gov/> (accessed Aug
606 1, 2013). 607
- (30) Suh, S. Developing a Sectoral Environmental Database for
608 Input–Output Analysis: The Comprehensive Environmental Data
609 Archive of the U.S. *Econ. Syst. Res.* **2005**, *17*, 449–469. 610
- (31) Lave, L. B.; Matthews, H. S. *Environmental Life Cycle Assessment*
611 *of Goods And Services: An Input–Output Approach*; Resources for the
612 Future: Washington, DC, 2006. 613
- (32) Jones, C. M.; Sullens, W.; Dryden, A.; Kantenbacher, J.;
614 Kammen, D. M. *Measuring the Climate Impact of Residential Buildings: The*
615 *GreenPoint Rated Climate Calculator Version 2*, Report prepared for the
616 California Air Resources Board 09-344; California Air Resources
617 Board: Sacramento, CA, 2012. 618
- (33) Ingram, D. D.; Franco, S. J. NCHS Urban-Rural Classification
619 Scheme for Counties. *Vital Health Stat.* **2012**, *2*, 1–65. 620
- (34) CoolClimate Carbon Footprint Calculator. CoolClimate
621 Network. <http://coolclimate.berkeley.edu/carboncalculator> (accessed
622 Aug 1, 2013). 623
- (35) Hertwich, E. G.; Peters, G. P. Carbon Footprint of Nations: A
624 Global, Trade-Linked Analysis. *Environ. Sci. Technol.* **2009**, *43*, 6414–
625 6420. 626
- (36) Lenzen, M.; Peters, G. M. How City Dwellers Affect Their
627 Resource Hinterland. *J. Ind. Ecol.* **2010**, *14*, 73–90. 628
- (37) Long, J. C.; John, M.; Greenblatt, J.; Wei, M.; Yang, C.; Richter,
629 B.; Hannegan, B.; Youngs, H. *California's Energy Future—The View to*
630 *2050*; California CCS Coalition: Sacramento, CA, 2011. 631
- (38) Wei, M.; Nelson, J. H.; Greenblatt, J. B.; Mileva, A.; Johnston, J.;
632 Ting, M.; Yang, C.; Jones, C.; McMahon, J. E.; Kammen, D. M. Deep
633 Carbon Reductions in California Require Electrification and
634 Integration across Economic Sectors. *Environ. Res. Lett.* **2013**, *8*,
635 No. 014038. 636