Do US metropolitan core counties have lower scope 1 and 2 CO$_2$ emissions than less urbanized counties?

M M Tamayao$^1$, M F Blackhurst$^2$ and H S Matthews$^{1,3}$

$^1$Department of Engineering and Public Policy, Carnegie Mellon University, 129 Baker Hall, Pittsburgh, PA 15213, USA
$^2$Department of Civil, Architectural and Environmental Engineering, University of Texas at Austin, 1 University Station C1752, Austin, TX 78712-0276, USA
$^3$Department of Civil and Environmental Engineering, Carnegie Mellon University, 119 Porter Hall, Pittsburgh, PA 15213, USA

E-mail: mtamayao@andrew.cmu.edu, mblackhurst@gmail.com and hsm@cmu.edu

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Abstract
Recent sustainability research has focused on urban systems given their high share of environmental impacts and potential for centralized impact mitigation. Recent research emphasizes descriptive statistics from place-based case studies to argue for policy action. This limits the potential for general insights and decision support. Here, we implement generalized linear and multiple linear regression analyses to obtain more robust insights on the relationship between urbanization and greenhouse gas (GHG) emissions in the US. We used consistently derived county-level scope 1 and scope 2 GHG inventories for our response variable while predictor variables included dummy-coded variables for county geographic type (central, outlying, and nonmetropolitan), median household income, population density, and climate indices (heating degree days (HDD) and cooling degree days (CDD)). We find that there is not enough statistical evidence indicating per capita scope 1 and 2 emissions differ by geographic type, ceteris paribus. These results are robust for different assumed electricity emissions factors. We do find statistically significant differences in per capita emissions by sector for different county types, with transportation and residential emissions highest in nonmetropolitan (rural) counties, transportation emissions lowest in central counties, and commercial sector emissions highest in central counties. These results indicate the importance of regional land use and transportation dynamics when planning local emissions mitigation measures.

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1. Introduction
At the confluence of both a changing climate and increased urbanization, cities have become a focal point for measuring and mitigating greenhouse gas (GHG) emissions [ICLEI 2011, UN 2011]. However, there exists considerable uncertainty about the link between geographic variation and GHG emissions. These uncertainties confound a richer understanding of the relationships between GHG emissions, emissions mitigation, and geographic change.

Early research on energy use and urban systems focused mainly on the transportation sector, where studies suggest reduced transportation energy requirements are associated with increased density, access to nonvehicle modes, and mixed land use planning (for examples see Pushkarev and...
Zupan 1977, Newman and Kenworthy 1989, Frank and Pivo 1994, Cervero and Kockelman 1997). With increasing empirical information on local GHG emissions, researchers started to include in-city (‘territorial’) emissions from additional end-uses in the late 2000s. Comparing residential plus personal transportation emissions from 66 major US metropolitan area, Glaeser and Kahn (2010) suggest that a household would produce lower GHG if it was in an urban area of higher population density, near city centers, in a location with moderate climate (i.e., warmer winter and cooler summer), and is serviced by cleaner electric utilities (i.e., less coal used for power production). Brown et al (2008) similarly found that the average metropolitan resident has lower per capita residential plus personal transportation emissions (2.24 tons yr⁻¹) than the average American (2.60 tons yr⁻¹), which the authors attribute to less car travel and electricity use. Expanding the scope of in-city emissions to include all buildings, on- and off-road transportation, and fugitive emissions from industry and waste management, Kennedy et al (2009) contrasted emissions for ten global cities, finding a five-fold difference in emissions per capita that was attributed to a combination of geophysical (climate and access to resources), socio-economic (population density and per capita income) and infrastructure factors (power generation and urban design).

Table 1. Source fuels, energy end-uses, and estimation methods per emissions scope.

| Emissions scope | Definition | Typical source fuels of emissions | Typical energy end-uses |
|-----------------|------------|----------------------------------|-------------------------|
| 1               | Emissions from direct combustion of fuels within a geographic boundary (‘territorial’ emissions) | Natural gas, gasoline, diesel, jet fuel | Home heating, cooking, on-and off-road transportation |
| 2               | Emissions from energy consumed within a geographic boundary generator elsewhere | Varies across the electrical grid | Lighting, air conditioning, appliances |
| 3               | Emissions embodied in imported goods and services and exported wastes | Varies within the supply chain of imported goods and services | N/A (energy embodied in the supply chain of imported good or service) |

More recent research has emphasized the challenge of isolating the effect of urbanization on local GHG emissions. Analyzing in-city emissions for 62 European cities, Baur et al 2014 challenged established correlations between emissions and population density, finding such correlations were highly sensitive to the geographic scale of the analysis as well as household occupancy and income. York et al (2003) apply simple linear regression to an expanded, log-log format of the IPAT identity (Impact = Population × Affluence × Technology) for 138 countries, showing emissions increase both with increasing urban populations and gross domestic product, with a possible Kuznets relationship between urbanization and emissions.

The impact of wealth creation and re-spending on urban emissions has recently been emphasized by researchers aiming to include emissions embodied in goods and services imported and exported across city boundaries. As summarized in table 1, emissions embodied in imports and exports are classified as scope 3, which differ from emissions that occur directly within a city boundary (scope 1 or ‘territorial’ emissions) and those directly associated with city energy demands but emitted outside the city boundary (scope 2). The allocation of scope 3 emissions to cities is estimated to increase their global emissions share to as much as 80% (Satterthwaite 2008); though other researchers caution that attributing such allocations purely to urbanization is likely misleading (Dodman 2009, Hoornweg et al 2011).

The inclusion of scope 3 emissions in local inventories has precipitated ‘trans-boundary’ and ‘consumption-based’ accounting schemes. Trans-boundary schemes include emissions estimates associated with imports of energy (scope 2) and select basic provisions such as example food, water, and building materials (Ramawami et al 2008; Ramaswami et al 2011, Chavez & Ramaswami 2011, and Hillman and Ramawami (2011)). Consumption-based inventories attempt to include emissions embodied in all imports and exports that cross geographic boundaries (Larsen and Hertwich 2009, Minx et al 2013).

Trans-boundary and consumption-based accounts use environmental life cycle assessment techniques to estimate scope 3 emissions attributed to imports and exports. Most studies emphasize case studies that include summary statistics of local GHG’s by emissions scope. In a more comprehensive consumption-based study, Minx et al (2013) utilize a multi-regional input–output model to estimate consumption-based emissions for all 434 municipalities in the United Kingdom (UK). They identify correlations between per capita footprints and occupancy, car ownership, and education. Minx et al (2013) find that scope 3 emissions are generally higher than territorial emissions (scopes 1 and 2) for most municipalities in the UK, independent of urban or rural geography and emphasize that consumption-based accounting has the effect of geographically homogenizing point emissions sources, namely industrial plants.

While the literature generally treats all emissions scopes equally, we emphasize a few important distinctions in the context of measurement and mitigation. First, policy actors—particularly local governments—have much less jurisdiction over scope 3 emissions than scopes 1 and 2. Second, emissions scopes 2 and 3 are scope 1 for producers located upstream in the supply-chain. The implications for this are twofold. It means no emissions can be reduced if all actors in the supply chain focus exclusively on scope 3 emissions.
Perhaps more importantly, it means that any and all features of scope 1 emissions—such as uncertainty and variation—are represented in emissions scopes 2 and 3, which is currently not yet reflected in mitigation planning (Blackhurst et al. 2011).

In addition to uncertainty and variation in scopes 1 and 2 (see Weber et al. 2010, Blackhurst et al. 2011, Siler-Evans et al. 2012), scope 3 emissions also include uncertainty and variation introduced by incomplete empirical data describing supply chains (Bullard and Sebald 1977, Basket et al. 1995); factors used to allocate final demand in space and time and by productive sector (Wilting 2012); an incomplete representation of international trade (Robbie et al. 2009, Lenzen et al. 2010, Weber 2008); representing production technologies and factor inputs as national and sector averages (Miller and Blair 2009, Weber et al. 2010, Siler-Evans et al. 2012); static supply chains (Bullard and Sebald 1977, Wood 2011); and price and currency conversions (Weber 2010). Since only several of these assumptions have been directly tested in the literature, the uncertainty and variation in currently reported scope 3 estimates is likely underreported, complicating a clear understanding of the relationship between urbanization and scope 3 emissions and confounding efforts to measure baseline scope 3 emissions, plan mitigation targets, and measure progress.

Finally, Kennedy and Corgée–Morlot (2013) indicate that additional capital expenditures in low-carbon infrastructure—which increases scope 3 emissions—has led to an observed decrease in emissions scopes 1 and 2. Such trade-offs have been established for many sources of discrete technical change in LCA (for examples see Keoleian et al. 2000, Pacca et al. 2007, Chester and Horvath 2009, Blackhurst et al. 2010). However, these connections have not yet been integrated into city-scale GHG measurement and respective decision-making, further challenging the approach of treating emissions scopes equally with respect to mitigation planning.

Further confounding insights into the connection between geographic variation and GHG emissions are differing and changing definitions of ‘urban’ and variation in the dynamics contributing to urbanization (Anderson et al. 1996, Morrill et al. 1999, Schneider and Woodcock 2008) as well as a lack of clarity in how metropolitan scale dynamics—such as regional land use planning and commuting—should be reflected in territorial emissions and respective mitigation planning.

As a result of the above uncertainties, differing definitions, and empirical limitations, the connection between geographic change and GHG emissions remains unclear. With this in mind, our objective is to identify any statistically significant variation in scope 1 and 2 emissions that can be explained by county-level geographic variation, using consistent geographic descriptors, controlling for previously identified sources of variation in emissions. This method is intended to serve as additional technical support behind future efforts with robust consideration of uncertainty for scope 1, 2, or 3 boundaries.

2. Methods

2.1. Geographic definitions

The US Census Bureau classifies counties as central, outlying, and nonmetropolitan (US Census Bureau 2011). Central counties are the most urbanized core in a Metropolitan Statistical Area (MSA). A central county is defined as having at least 50% of its population in urban areas with population of at least 10,000 or containing at least 5,000 residents in a single urban area with population of at least 10,000. Meanwhile, Outlying counties are located in an MSA if they meet certain requirements of social and economic integration with one or more of the central counties in the MSA, such as regional commuting to central counties. Counties not included in an MSA are classified as nonmetropolitan counties (generally rural areas). Detailed definitions for these designations are available from the US Census Bureau (2011). A map of the US showing the different MSA types is provided in appendix A in the supplementary data, available at stacks.iop.org/ERL/9/104011/mmedia.

2.2. County level CO₂ data

The emissions inventories used here include direct emissions (scope 1) and indirect emissions from electricity consumption (scope 2). Scope 1 GHG emissions estimates for the 3,141 counties in the US for 2002 were obtained from Project Vulcan, a database that provides a county-level resolution of production-based emissions from fossil fuel combustion by aggregating publically available data from EPA, DOE, etc. Gurney et al. (2009) provides a discussion of the methodology in deriving this database, which has predominantly been used for much finer resolution modeling of individual facilities. Scope 1 emissions are reported by sector: residential, industrial, commercial, and onroad, nonroad, and air transportation. Emissions from agriculture and waste management were not included in this analysis.

Scope 2 emissions were computed as the product of county-level electricity consumption and electricity emissions factors. We used multiple regression model to estimate electricity consumption, c_i, for each county i with general form shown in (1).

\[ c_i = \beta_0 + \beta_1 \text{Population}_i + \beta_2 \text{Econ}_i + \beta_3 \text{Climate}_i + \epsilon_i \]

Predictor variables included population (Pop), population density (PopDensity), economic indicators (EconInd) (e.g., total payroll, household aggregated income, number of employees, number of establishments, total sales), climate indices (ClimateInd) (e.g., heating degree days (HDD) and cooling degree days (CDD)), and the interaction between population climate indices (PopClim). The model that resulted in the most accurate prediction of electricity consumption is shown in (1), where i is the county identifier, c_i, is the electricity consumption, Pop is population, Pop*HDD is the interaction between Population and HDD). County level electricity consumption data used for modeling include publicly available data constituting all California counties (2006–09), all Vermont counties (2006–09), five Illinois counties (2005), and King County, Washington (2005–09). The main criterion for final model selection is...
The electricity emissions factor is a function of the fuels used to generate electricity consumed at the county scale. It is nontrivial (some authors suggest not possible) to associate a given county’s electricity consumption with specific generation assets to derive an emissions factor (Weber et al 2008). Electricity generally flows freely within operating regions defined by the North American Electric Reliability Corporation, often referred to as the ‘NERC regions’, but little electricity generally crosses these regions (Marriott et al 2010). Thus, emissions factors must be estimated for geographic regions smaller than the NERC regions. We thus present results using emissions factors for NERC regions but conduct a sensitivity analysis using emissions factors defined for eGRID subregions (eGRID 2004) and US states (eGRID 2004).

A total of 618 counties, about 6% of the US population, (Outlying = 6, Nonmetropolitan = 612) were omitted as outliers during model diagnostics and selection for electricity consumption prediction.

2.3. Regressing emissions vs. urbanization level

The most general form of our model describing predictors of county GHGs is shown in equation (2). Regressions were performed for both total and capita emissions using equation (2)

\[
\begin{align*}
\text{GHG}_{i,j} &= \beta_0 + \beta_{\text{Geo1}} \text{Geo1}_i + \beta_{\text{Geo2}} \text{Geo2}_i \\
&+ \beta_{\text{HH GDP}} \text{HH GDP}_i \\
&+ \beta_{\text{Pop DENSITY}} \text{Pop DENSITY}_i \\
&+ \beta_{\text{HDD}} \text{HDD}_i + \beta_{\text{CDD}} \text{CDD}_i + \epsilon_i. 
\end{align*}
\]

(2)

where \( \text{GHG}_{i,j} \) is total or per capita scope 1 and 2 emissions for county \( i \) for either all sectors or by sector \( j \) in residential, commercial, industrial, onroad, nonroad, and air transportation, and electricity consumption, \( \text{HH GDP}_i \) is the median household income, \( \text{Pop DENSITY}_i \) is the population density, \( \text{HDD}_i \) is the heating degree days, \( \text{CDD}_i \) is the cooling degree days, and \( \text{Geo1}_i \) and \( \text{Geo2}_i \) are the dummy codes for county geographic types - central, outlying, and nonmetropolitan. We controlled for other variables (i.e., HDD/ CDD, population density, and income), which have been shown in previous works to have a significant relationship with energy consumption (e.g., Quayle and Diaz 1980, Eto 1988, Carson et al 1997, Sailor & Munoz 1997, and Zhang 2004 to name a few). By varying the reference geographic type, we used this model to determine whether there is significant difference between mean emissions (i.e., coefficients are significant) stemming from geographic variation.

For example, with type ‘central’ as the reference, Geo1 = outlying and Geo2 = rural, and regression results for \( \beta_{\text{outlying}} \) and \( \beta_{\text{rural}} \) indicate differences between emissions levels associated with outlying and rural counties relative to central counties, all else equal. The coefficients were evaluated at 5% significance level.

Model screening indicated the assumptions for ordinary least squares do not hold. We elected not to transform variables to promote an intuitive interpretation of the relationship between geographic type and local emissions. Best models were found using both linear regression model (using robust regression) and generalized linear model (GLM) techniques, using the Inverse Gaussian family.

Due to observed correlations between independent variables, some were dropped from equation (1). We found weak correlations between geographic type and both median household income and population density. This is likely because the MSA classification we used, as defined by the US Census Bureau (2011), is partly based on population density. Previous works suggest a positive relationship between urbanization and income (Jones and Kone 1996, Bloom et al 2008, Glaeser 2011). But Bloom et al (2008) provides the caveat that nascent stages of urbanization are not correlated with income growth, which may explain the weak correlation we found. We also found weak correlation between median HH income and population density, indicating a relationship between urbanization, income, and population density. Meanwhile, moderate negative correlation between HDD and CDD was observed. In model selection, we dropped some of these variables to avoid multicollinearity. The retained variables were selected based upon maximizing goodness-of-fit (Adjusted R² and Akaike Information Criterion (AIC)). We provide additional information on data used in appendix C and further discussion on model fitting, diagnostics, and selection are presented in appendix D.

3. Results and discussion

Regression results for per capita scope 1 and 2 emissions for all sectors are summarized in table 2. The intercept is interpreted as the average per capita emissions in central counties while the coefficients for the other geographic types indicate differences from central counties (e.g., avg. nonmetropolitan per capita scope 1 and 2 emissions (last column) is central county avg. per capita scope 1 and 2 emissions (22.81) plus nonmetropolitan coefficient (0.11) which is equal to 22.92 tons CO₂ persons yr⁻¹). Regression results presented here correspond to a reduced (less predictor variables, outliers and influential variables excluded) model which we most appropriate to use in our analysis, as in the case of Minx et al (2013).

In the residential and transportation (onroad, nonroad, and air) sectors, per capita emissions in nonmetropolitan counties are the highest. Mean per capita direct residential emissions are about 4% ((1.67 tons CO₂ per capita—1.6 tons CO₂ per capita) higher in central
Table 2. Sector per capita emissions regression analyses results (Y2002).

| Variable       | Industrial | Residential | Commercial | Transportation onroad | Transportation nonroad | Transportation air | Scope 1 | Scope 2 NERC | Scope 1 + 2 NERC |
|----------------|------------|-------------|------------|-----------------------|------------------------|-------------------|---------|---------------|------------------|
| Intercept      | 3.28***    | 1.67***     | 1.13***    | 4.62***               | 0.32***                | 0.13*             | 11.62***| 10.91***      | 22.81***         |
|                | (0.08)     | (0.07)      | (0.16)     | (0.14)                | (0.06)                 | (0.06)            | (0.95) | (0.52)        | (1.06)           |
| Nonmetro       | 0.49 (0.03)| 0.17***     | -0.16*     | 2.09***               | 0.64***                | 0.06*             | 3.38***| -3.27***      | 0.11 (0.44)      |
|                |            | (0.03)      | (0.06)     | (0.12)                | (0.03)                 | (0.03)            | (0.39) | (0.22)        |                 |
| Outlying       | -0.35 (0.41)| -0.07 . | -0.43***   | 1.45***               | 0.15***                | -0.07 .            | -0.89 . | -0.34 (0.28)  | 0.59 (0.57)      |
| Med. HH Pop. Dens. | -2.02e-05 | 8.57e-06***| 6.26e-06*  | 1.21e-06               | 6.55e-06*              | 3.94e-06**         | -7.80e-06 | -3.53e-06    | -1.60e-05       |
|                | (1.40e-05) | (1.23e-06) | (2.84e-06) | (1.23e-06)            | (1.23e-06)            | (9.47e-06)        | (1.73e-05) | (9.12e-05)   |                 |
| CDD            | 4.32e-04   | -5.22e-04***| -3.20e-04***| 3.70e-04***           | -2.06e-04***           | -1.09e-04          | -1.44e-04 | -3.27e-04    |                 |
|                | (1.59e-04) | (1.39e-05) | (3.22e-05) | (7.95e-05)            | (1.23e-05)            | (1.96e-04)        | (1.07e-04) | (2.16e-04)   |                 |
| HDD            |            |             |            |                       |                        |                   |         |               |                  |
|                |            |             |            |                       |                        |                   |         |               |                  |
| AIC            | 15523      | 3465.1      | 7632.9     | 11178                 | 2946.8                 | 3740.9            | 16567   | 13586         | 16444           |
| Adj. or Pseudo R² | 0.01      | 0.44        | 0.06       | 0.09                  | 0.13                   | 0.01              | 0.04    | 0.13          | 0.05            |
| Model          | LRM        | LRM         | LRM        | GLM                   | LRM                    | LRM               | LRM     | GLM           | LRM             |

Signif. Codes: 0 *** 0.001 ** 0.01 * 0.05 . .
countsies than outlying counties, ceteris paribus. The opposite is true in the onroad and nonroad transportation sectors, where outlying counties have higher per capita emissions by about 45% and 33%, respectively. Potential reasons for this observation are varying land use patterns, density, and access to transit and nonmotorized modes (Pushkarev and Zupan 1977, Newman and Kenworthy 1989, Frank and Pivo 1994, Cervero and Kockelman 1997).

In the commercial sector, outlying counties were found to have the lowest average per capita emissions, ceteris paribus—about 36% and 43% lower than central and nonmetropolitan counties, respectively. Central counties were found to have the highest commercial sector emissions, although at only 2% higher than nonmetropolitan counties, ceteris paribus. This could be due to the role of central counties serving as regional centers of commerce.

We did not find enough statistical evidence to say that industrial emissions differ by urbanization level. For scope 2, we find per capita emissions in central counties to be similar to outlying counties but 40% higher in nonmetropolitan counties. That is, we find metropolitan residents have more emissions from electricity consumption than rural residents. For electricity, these results are robust with parametric variation in emissions factors assuming different electricity grid regions (states, NERC regions, or eGRID regions).

Importantly, contrary to previous findings, we find no statistically significant relationship between geographic variation and total scopes 1 plus 2 per capita emissions. These results are robust across parametric variation in the emissions factor and regression methods. Even if we relax the need for statistical significance, the predicted values indicate a maximum of 3% difference by geographic type.

As shown in table 2, we controlled for income instead of dropping it entirely, noting that we found very weak correlation between urbanization and income; also, previous works suggest caution in emphasizing this relationship (Bloom et al 2008). But to further check the robustness of our conclusions, we looked at the results when income is dropped from the equation. The coefficients for the geographical types changed (i.e., estimates for per capita emissions by MSA level changed) but we still did not find enough statistical evidence to suggest relationship between urbanization and total scope 1 and 2 emissions.

Figure 1 summarizes predicted per capita emissions by sector using models specified in table 2. As shown, the mean total scope 1 and 2 in central counties, 22.8 tons CO$_2$ yr$^{-1}$, is slightly lower than that of outlying and nonmetropolitan counties—23.4 and 22.9 tons CO$_2$ yr$^{-1}$, respectively—but the spread of central county emissions values is much wider. Table 3 summarizes ratios of estimated per capita emissions by both sector and geographic type.

Figure 2 shows variation in per capita emissions given population density. Similar to the empirical findings, these trends generally show a decrease in per capita transportation emissions with increasing density; however, emissions per capita for buildings trend upward with increasing density. Marginal changes for the transportation and buildings sectors decrease significantly around 300 persons/sq. mi. (log $300 \approx 2.5$) and 100 persons/sq. mi. (log(100) = 2). We did the same for scope 1 and 2 per-capita emissions versus population density and found that decrease in marginal emissions become marginal at about 600 persons/sq. mi. While the uncertainty and variation in these data are large, these trends indicate there could be diminishing marginal changes to emissions with increasing population density and such changes vary by end-use sector. Fragkias et al (2013) recently reached similar conclusions with respect to total MSA size, where total emissions and population were found to scale proportionally for a cross-sectional analysis of MSA emissions from 1999–2008.

These results highlight the importance of considering metropolitan dynamics in the context of local climate action planning. Central counties often serve as regional centers of commerce (higher commercial sector emissions), which induces regional transportation demands from trips originating in outlying and nonmetropolitan counties. Regional land use planners may be interested in shifting commerce to outlying and nonmetropolitan counties with the intent of reducing transportation demands in these counties. However, this may increase commercial sector emissions in outlying counties with unclear implications for transportation and commercial emissions in central counties. Our data are limited to...
cross-sectional analyses for a single year; thus the temporal
dynamics of such land use change remain unclear. Sig-
nificantly more empirical data would be required for a time-
series (panel) regression.

We also emphasize the importance of uncertainty in local
emissions estimates ('GHG inventories') for planning emis-
sions reductions. Assigning the various reported emissions
factors at the county level, we found an average change from
the base case (using NERC emissions factors) of about
13–15%. Thus, similar to other studies, we
find using inap-
propriate emissions factors may be misleading when mea-
suring and planning emissions reductions at the local scale
(Katherine and Sundquist2008, Blackhurst et al
2010, Mar-
riott et al
2010 and Weber et al
2010). This partial accounting
of uncertainty in total emissions is well within the range of
planned GHG reduction targets (ICLEI2012), thus compli-
cating planners’ ability to set representative baseline emis-
sions and to benchmark changes to emissions. Thus, planning
methods that do not re
fl
ect inherent uncertainty in baseline or
expected emissions factors may be misleading.

Future work could include estimates of Scope 3 emis-
sions to provide a more comprehensive estimate of the GHG
implications of urbanization; however, estimates of scope 3
emissions of similar empirical quality or missing and unlikely
to be available soon. Nevertheless, one would expect total
scope 3 emissions to be higher for urban systems given the
more intensive material requirements for urban infrastructure
(Minx et al
2013). Given that our regression results show that
per capita scope 1 and 2 emissions do not differ by urbani-
zation level, it is likely that when scope 3 emissions are
included, per capita emissions in more urbanized counties
could actually be much higher, on average, compared to less
urban counties.

Based on our results, we believe that a more focused
effort on reducing per capita emissions related to US core
metropolitan counties, especially the larger ones, is justified.
Although our work is specific to the context of the US, the
rapid pace of urbanization the world over calls for more work
on figuring out the extent and form of urbanization that is
sustainable.

Figure 2. Population Density versus a. transportation sector scope 1 emissions and b. emissions from the buildings sectors plus all scope 2 emissions (excluded Wilcox County, AL because of outlier per capita emissions value >2000 tons yr⁻¹).

Table 3. Comparison of per capita emissions by urbanization level
(Cell values = ratio (row/column) of average county type emissions; Red: Row > Col, Green: Row < Col; Gray: NS difference [NS]).

| Ratios For Average Per Capita Emissions | Industrial | Residential | Commercial | Onroad | Nonroad | Airport | Electricity | Scope 1 + 2 |
|-----------------------------------------|------------|-------------|------------|--------|---------|---------|------------|------------|
| Central                                 | NS         | 1.0         | 1.6        | 0.8    | 0.8     | 2.2     | NS         | NS         |
| Outlying                                | Nonmetro   | 0.9         | 0.7        | 0.7    | 0.5     | 0.7     | 1.4        | 1.4        |
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