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Urban Form as a Technological Driver of Carbon Dioxide Emission: A Structural Human Ecology Analysis of Onroad and Residential Sectors in the Conterminous U.S.

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Received: 28 July 2020; Accepted: 11 September 2020; Published: 21 September 2020



Abstract: This study investigates the role of urban form as a technological driver of U.S. CO₂ emissions for the onroad and residential sectors. The STIRPAT (Stochastic Impacts by Region on Population, Affluence, and Technology) human structural ecology framework is extended by drawing from science and technology studies (STS) to theorize urban form as a sociotechnical system involving practices and knowledge that contribute to urban land use as a material artifact on the landscape influencing emissions. Questions addressed are: (1) “What is the influence of urban form on total sector CO₂ emissions?” and (2) “How does the influence of urban form on CO₂ emissions differ for metropolitan versus non-metropolitan status?” Spatial error regression models were estimated using county-level CO₂ emissions data from Project Vulcan. The National Land Cover Dataset (NLCD) was used to quantify measures of urban form. Other independent variables were derived from U.S. Census data. Results demonstrate carbon reduction benefits achievable through a developed land use mix containing a greater proportion of high intensity relative to low intensity use. Urban form matters, but it matters differently in terms of sign, significance, and interpretation depending on emission sector and metro versus non-metro status. A focus on urban form provides policymakers potential leverage for carbon mitigation efforts that focus on total emissions as opposed to per capita emission. A feature of the research is its integration of concepts and theory from structural human ecology, STS, land change science, and GIScience.

Keywords: CO₂ emissions; urban form; STIRPAT; socio-technical system; land change science; GIScience

1. Introduction

Anthropogenic greenhouse gas (GHG) emission is the major contributor to global climate change [1], with urban areas contributing a majority share of emissions [2,3]. Researchers across disciplines have sought to understand carbon emission effects of population, income, technology, and energy intensity using the Kaya Identity, the IPAT identity, and the STIRPAT framework [4]. The Kaya Identity is an equation for computing the total carbon dioxide (CO₂) emissions caused by humans for a defined region, and is named after its originator Yoichi Kaya [5,6]. It expresses total emission levels as the product of four factors: Human population size, GDP per capita, energy intensity (per unit of GDP), and carbon intensity (emissions per unit of energy consumed). The Kaya identity is an application of the IPAT identity ($I = PAT$) [7,8], which relates human impact on the environment (I) to the product of population (P), affluence (A), and technology (T). Empirical research has extended IPAT to estimate drivers of CO₂ emission using statistical regression techniques follow the STIRPAT framework [9,10], which is described in a following section. STIRPAT is an acronym for Stochastic Impacts by Region on Population, Affluence, and Technology.

Debate exists regarding carbon efficiencies of urban areas versus non-urban areas; and further, if larger cities (by population) are more carbon efficient than smaller cities [11–13]. STIRPAT statistical models estimate regression coefficients that quantify the effects of population on CO₂ emissions, as well as effects from other variables. Effects of population size are estimated by the population variable's regression coefficient β . Coefficients of $\beta = 1.0$ indicate a linear relationship where emissions grow proportionately with population size. Coefficients with $\beta < 1.0$ indicate a more carbon efficient and thus desirable supralinear relationship suggesting economies of scale due to urban agglomeration where emissions grow less than proportionately with population size. Coefficients with $\beta > 1.0$ indicate a superlinear relationship suggesting an undesired situation where emissions grow more than proportionately with population size.

Urban population's scaling relationship can be contradictory across research due to methods used to define urban boundaries and population. Louf and Barthelemy [14] demonstrate the presence of both supra and superlinear relationships depending on how one defines the city, alternatively using U.S. Census definitions of "metropolitan statistical areas" and "urban areas". Model specification can be another complicating factor. Consider Oliveira et al. [12] (2014), who state that "Large cities are less green" due to findings of superlinear relationships with an average $\beta = 1.46$ across multiple models for U.S. cities. A key innovation was their use of the City Clustering Algorithm (CCA), a geospatial method yielding city spatial extents from gridded population data and a spatial contiguity parameter, as opposed to the imposition of administrative boundaries. Oliveria et al. [12] contradict research showing reduced emission benefits of urbanization. Given that the IPAT/STIRPAT framework includes other factors (e.g., affluence and technology), there is the concern of omitted variable bias in models limited to just population or population and affluence. How would results differ with a more fully specified model?

Fragkias et al. [11] similarly ask, "Does size matter? Scaling of CO₂ emissions and U.S. urban areas" using metropolitan and micropolitan areas as spatial units. Models with measures of affluence and population using times-series emissions data for 1999–2008 yield population scaling coefficients close to $\beta = 1.0$. The linear scaling relationship suggests an absence of urbanization's benefits (but no disadvantages). Contradictory findings might be explained by differing methods to define spatial units of analysis. Oliveira et al. [12] argue that city units derived from the CCA method are more appropriate than use of administrative boundaries such as the metropolitan statistical area (MSA) because MSAs include significant areas with population that are neither urban nor located in cities.

This research aims to advance understandings of drivers of CO₂ emissions by investigating the role of urban form, which is theorized to represent an important role of technology influencing CO₂ emissions. I use U.S. CO₂ emissions data for the residential and on-road transportation sectors from the Project Vulcan dataset [15], a bottom-up data product widely used in the research community, including by [12] and [11]. The main objective is to understand the effects of urban form using measures of developed land use, although population and other factors are included in empirical analysis. Attention is given to assess whether effects of developed land use and population are supralinear, linear, or superlinear. Two research questions are posed:

- (1) What is the influence of urban form on CO₂ emissions in the conterminous U.S.?
- (2) How does the influence of urban form on CO₂ emissions differ for metropolitan versus non-metropolitan status?

Goals of this research are to theorize and empirically evaluate urban form as a technological driver of CO₂ emissions. Explicit inclusion of urban form as a technological driver is both theoretically relevant and an important step towards more fully specified models that can reduce omitted variable bias. Urban form is defined here as the composition (i.e., how much of different types) and configuration (i.e., spatial pattern) of developed land use. Urban form (or urban morphology) research has a rich history that studies the form of human settlements and the process of their formation and transformation [16]. Researchers and professionals from the fields of geography, urban design,

city/town planning, architecture, and others investigate urban form at a variety of scales ranging from a cluster of buildings, to a neighborhood, and to an urban region [16]. This research operates at a regional landscape scale using counties as the unit of analysis. County units impose administrative boundaries that are not fully reflective of functional urban regions. However, use of counties enables use of observable data that justifies this approach which, compared to the finer scales of building clusters or neighborhoods, can be considered at the regional landscape scale.

Much of the carbon emissions research focuses on urban areas [2,3,17,18], most often measuring urbanization using levels of population defined as urban from census data. Relatively less research approaches the urban question using land use data to characterize urban form, although see [19–26]. Generally, this empirical work shows that urban areas with more sprawl-like urban form are associated with higher emission levels. It is not common for research to make an explicit theoretical case for the role of urban form as a technological driver and drawing on concepts from the field of science and technology studies (STS) [27]. This research makes such a case, and uses the STIRPAT framework to empirically analyze the effects of urban form on U.S. CO₂ emissions.

I extend the STIRPAT human structural ecology paradigm [9,10] to include the role of urban form as a technology driver. A key methodological contribution promotes the technique of spatial error regression [28] as particularly appropriate for STIRPAT analyses due to difficulties with specifying unambiguous technology (and other) variables. To preview findings, results demonstrate carbon reduction benefits associated with a developed land use mix containing a greater proportion of high intensity land use relative to low intensity land use. A notable feature is the use of land use data derived from remote sensing classification for measures of urban form and population and household density. The approach of using land use data resonates with Horner et al. [29], who call for an integrated GIScience and energy research agenda to respond to climate change.

1.1. IPAT and STIRPAT

Studies of human environmental impacts have been framed within a theoretical context of structural human ecology that theorizes impacts using the multiplicative IPAT identity [30] in models of greenhouse gas emissions:

$$I = P \times A \times T \quad (1)$$

where I represents environmental impact, A represents affluence, and T represents technology [7,8,30]. For CO₂ emissions as the focal impact, this identity can be expressed as:

$$CO_2 = Population \times GDP/Population \times CO_2/GDP \quad (2)$$

A criticism of IPAT is that it is an accounting identity that, assuming perfect measurement, is tautological and, by definition, must balance on each side of the equation [30]. Response to IPAT critics led to reformulation into a stochastic form termed STIRPAT, which is an acronym for Stochastic Impacts by Regression on Population, Affluence, and Technology [9,10,31–33]. The general STIRPAT model is specified as:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (3)$$

The constant a scales the model, and b , c , and d are exponents that must be estimated, while e is the error term. The subscript i denotes the spatial observation unit. Research using time series data extends specification with appropriate notation for time. Logarithmic transformation enables estimation via additive regression modeling. Due to difficulties in measurement and interpretation of technology [34,35] some researchers have stated that T can be excluded and instead represented in the error term, rather than estimated explicitly, as in the following model shown with log transformed terms [32], where coefficient estimates represent elasticities:

$$\log I_i = a + b(\log P_i) + c(\log A_i) + e_i \quad (4)$$

STIRPAT models often extend this basic model to test hypotheses including contextual and control variables beyond just population and affluence [31,36,37]. The residual error e is implicitly a catch all term reflective of unobserved aspects of technology and other non-technological variables. A potential problem with treating the error term in this manner is the possibility of spatially autocorrelated residuals. Autocorrelated residuals violate regression assumptions and can cause biased and erroneous parameter estimates [38]. When working with spatial data and underspecified models, there are sound reasons to expect that residuals should be positively autocorrelated. Most STIRPAT emission studies use regression techniques that ignore the potential of spatially autocorrelated residuals. Spatial regression techniques have emerged that can help address this problem [28,38] and have entered the STIRPAT literature [34,39].

1.2. Theory—Urban Form as Technology

I draw from the field of science and technology studies (STS) [27] to argue the role of urban form as technology. A basic definition of technology is that “Technology is the process by which humans modify nature to meet their needs and wants” [40] (p. 2). Urban land use is argued here to be an important representation of technology due to historical and ongoing conversion of land to provide housing, infrastructure, commercial spaces, and other amenities of the built environment. Technology is comprised of three components: Artifacts, practices, and knowledge [41]. Artifacts are the material objects produced by humans. Tools and devices such as cars, televisions, or smart phones are examples of artifacts commonly associated with technology in the popular mindset. Here, land use patterns exemplify the concept of artifacts. Land use practices that create human-modified landscapes and infrastructure constituting urban form fulfill the definition of practices as a second component of technology. Practices are the “on the ground” construction methods used to produce urban land use and urban form as well as practices of local or regional planning commissions, the real estate industry, business interests, and consumers. Knowledge represents the underlying theories and paradigms that influence technology in different settings [41]. Such knowledge is embodied within the scholarship and applied practice of urban/regional planning, construction management, public administration, and business administration. Various actors in the system also hold non-professional knowledge, including consumers.

Technology can also be viewed as a more comprehensive sociotechnical system [42–44]. Kline [44] (p. 216) defines a sociotechnical system of manufacturing as “All the elements needed to manufacture a particular kind of hardware, the complete working system including its inputs: people; machinery; resources; process; and legal, economic, political and physical environment”.

Similarly and within an energy context, Winner [45] (p. 271) describes a technological system stating:

To provide the variety of goods and services that sustain them, modern societies have created elaborate sociotechnical systems that link production, distribution, and consumption in coherent patterns. Within such systems, the activities of work, management, finance, planning, marketing and the like are coordinated in highly developed institutional arrangements. These institutions, together with the physical technologies they employ, can be well characterized, borrowing a term from political theory, as “regimes” under which people who use energy are obliged to live.

The myriad of interacting actors and processes involved in the production and consumption of developed land use form the sociotechnical system responsible for settlement patterns and urban form expressed materially on the landscape. Selected actors would include builders, realtors, investors, bankers, consumers, planners, and politicians all behaving within legal, political, and institutional contexts.

While I position urban form within the context of science and technology studies, it is important to recognize that research from the fields of regional science and planning have examined relations

between urban form, accessibility, and technology, albeit from a different methodological approach than the STIRPAT structural human ecology approach presented here [46–48].

1.3. Prior Empirical Findings

A large body of STIRPAT literature examines drivers of carbon emissions. Much of this work is at the aggregate national level using either cross-sectional or panel time series data. Selected examples include [31,49–55]. Other studies focus explicitly on urban or metropolitan areas, which is an important research area given that cities account for the dominant share of global emissions [56–61].

1.3.1. Transportation Emissions

Prior research has shown that higher population density is associated with lower emissions due to more compact settlements entailing shorter driving distances, and, for larger and denser cities, greater shares of trips made by public transportation that are more carbon efficient [57,61–63]. The National Research Council report *Driving and the Built Environment* [64] (p. 3) states, “More compact, mixed-use development can produce reductions in energy consumption and CO₂ emissions both directly and indirectly” and that [64] (p. 2) “doubling residential density across a metropolitan area might lower household VMT [vehicle miles traveled] by about 5 to 12 percent, and perhaps by as much as 25 percent, if coupled with higher employment concentrations, significant public transit improvements, mixed uses, and other supportive demand management measures”.

Research by [65] examines drivers of travel behavior and the built environment, focusing on the “three Ds” [66] of density, diversity, and design, along with destination accessibility and distance to transit. Density is population, dwelling units, or employment per areal unit. Diversity pertains to the number of different land uses in a given area. Design measures street network characteristics. Findings revealed relationships between travel variables and the built environment to be small and inelastic, although vehicle miles traveled (VMT) was most strongly related to destination accessibility and secondarily to street network design. Other research [67] argues that lack of mobility choices is related to urban form and has developed a mobility choices model integrating urban form and accessibility indicators with choice of travel mode, carbon emissions, and transportation energy use. This approach [67] is argued to have potential to inform urban transformation and redesign that provides more sustainable travel alternatives. Transport modelling approaches have been used to estimate carbon emissions [68,69]. This work explicitly focuses on transport energy demand and emission outcomes incorporating scenarios and empirical data on transport demand, vehicle stock, and related emissions, and vehicle life cycle to model environmental impact.

1.3.2. Residential Emissions

Residential energy use/emissions research generally shows that housing size/type is related to energy consumption with larger single-family detached homes consuming more energy due to inefficiencies from greater surface to volume ratios compared to multi-family or single-family attached housing [3,70–72]. Ewing and Rong [71] provide a conceptual framework that links urban form to size/type of housing stock, which in turn influences residential energy consumption. From a supply side perspective, denser compact areas entail higher land prices so that suppliers may favor production of multi-family or single-family attached housing to reduce production costs [73]. Alternatively, higher land prices may influence suppliers to build larger houses, albeit on smaller lots (i.e., building vertically) [74]. From a demand perspective, consumers in more expensive dense/compact areas may have less disposable income, leading to a reduction in house size [75]. Alternatively, they may opt for larger housing due to lower transportation costs in denser areas [76].

Ewing and Reid’s conceptual model [71] also links urban form and residential energy consumption to local temperatures and specifically the urban heat island (UHI) effect (see [77]). In general, greater areal coverage of impervious surface causes radiant heat emissions that can act to elevate local temperatures relative to lower intensity development with more greenspace. Thus, all else being

equal, areas with greater impervious surface can be expected by the UHI effect to have slightly elevated temperatures, leading to lower energy consumption for home heating during the cold season. During summer months, elevated temperatures would have the opposite effect due to increased space cooling demand.

Simulation modeling applied to a sample of 500 m × 500 m residential sites in Paris, London, Berlin, and Istanbul has modeled heat-energy demand [78]. Sites spanning a range of urban forms and designs were strategically selected. Results for this neighborhood scale analysis suggested significant differences in heat-energy efficiency, with compact and tall buildings having the greatest efficiency, and detached housing having the lowest.

1.3.3. 1990–2017 Trends of Greenhouse Gas Emissions

The United States for many decades was world’s largest emitter of CO₂ from fossil fuel use until being surpassed by China in 2006 [79]. U.S. CO₂ emissions from 1990 to 2017 have consistently accounted for approximately 80% of all U.S. greenhouse gas emissions, with total and per capita CO₂ emissions trending upwards until 2007, followed by a declining trend [80]. Table 1 reports emission data for selected years and sectors, including the focal year 2002 for this research. The electricity and transportation sectors consistently were the top two ranked CO₂ emission sectors. Mean percentages of total CO₂ emissions by sector for the years 1990–2017 were electricity—37.2%, transportation—30.1%, residential—6.1%. Electricity and residential total and per capita emissions declined after 2002 to levels lower than 1990. Transportation’s total emissions for 2002 and 2017 are essentially identical, though per capita emissions declined.

Table 1. CO₂ emissions for selected sectors and years.

Year	All Sectors CO ₂ Emissions ¹		Electricity CO ₂ Emissions ²		Transportation CO ₂ Emissions ²		Residential CO ₂ Emissions ²	
	Total	Per cap	Total	Per cap	Total	Per cap	Total	Per cap
1990	5121.2	20.5	1819.5	7.3	1469.1	5.9	338.2	1.3
2002	5942.4	20.6	2272.1	7.9	1799.9	6.2	360.3	1.2
2017	5270.7	16.2	1732.0	5.3	1800.6	5.5	294.5	0.9

¹ Total emission in million metric tons; per capita in million metric tons per 100 million population. ² Total emissions from fossil fuel combustion in million metric tons; per capita in million metric tons per 100 million population.

2. Materials and Methods

2.1. 1990–2017 CO₂ Emissions Data

County-level data estimating CO₂ emissions in 2002 were obtained from Project Vulcan [15]. Data are currently provided publicly for the year 2002, available at either the county or 10 km gridded scale. The cross-sectional use of Vulcan’s 2002 data is justified in this research by the theoretical and empirical goals of understanding the role of urban form as a technological driver. Future work would benefit from richer time depth to investigate change. Gurney et al. [15] report that the Vulcan data align well with national level estimates produced by the U.S. Department of Energy’s Energy Information Agency (DOE/EIA) being within 0.1% of the DOE/EIA total and with good agreement for all sectors.

Emission sectors included in the Vulcan data include: Onroad, residential, nonroad, industrial, commercial, aircraft, cement production, electricity, and air transportation. Two sectors, onroad and residential, are used for analysis because they are more amenable to theoretical and empirical interpretation related to urban form. Onroad emissions are those occurring on roadways and exclude other forms of transport such as trains, marine vehicles and airplanes. Residential emissions reflect fossil fuel used largely for space and water heating, and represent emissions produced on site. Residential emissions associated with electricity consumption produced off-site, typically at fossil fuel power plants, are not included in this sector even though electricity is consumed on site at housing units.

Thus, residential emissions analyzed here largely reflect the subset of emissions related to space and water heating, which is substantially smaller than total onsite residential emissions if electricity consumption was included.

2.2. 1990–2017 CO₂ Spatial Emission Patterns

The present analysis includes the 3108 conterminous U.S. counties with 905 defined as metropolitan and 2203 as non-metropolitan by the U.S. Census. Emission patterns using Vulcan’s 10 km gridded data product are shown in Figure 1, revealing concentrations of high emissions in the more populated and urbanized Northeast, Midwest, and West Coast regions, as well as linear patterns associated with major transportation arteries. While distributions are rendered in gridded form for greater clarity, STIRPAT modeling was conducted at the county aggregated level. Inclusion of both metro and non-metro counties is justified because the vast majority of non-metro counties contain urbanized areas, albeit at smaller sizes. Vulcan’s total conterminous U.S. emissions in 2002 were 1585 million tonnes for the combined onroad and residential sectors. Alaska and Hawaii accounted for only 0.01% of this total and are excluded from analysis. Metropolitan counties accounted for 70% of emissions for these two sectors (Table 2). Within the Vulcan data, electricity accounts for the greatest share (38.9%), with onroad and residential emissions at 25% and 6%, respectively (Table 2). Differences in metro versus non-metro shares for electricity emissions are explained by the greater presence of electrical power plants in non-metro counties.

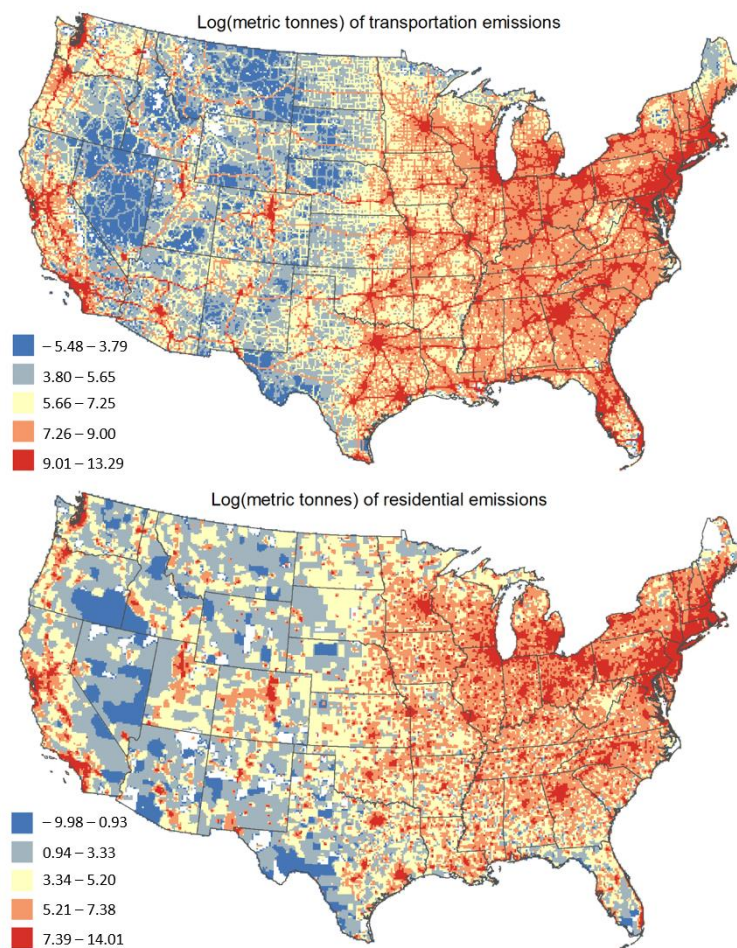


Figure 1. CO₂ emissions for onroad transportation and residential sectors, 2002.

Table 2. CO₂ emissions as percent of total emissions by sector, 2002.

	Conterminous U.S.	Metropolitan	Non-Metropolitan
Electricity	38.89	34.15	50.20
Onroad	25.09	27.33	19.74
Industry	17.70	17.92	17.19
Residential	6.39	7.45	3.84
Commercial	4.14	4.84	2.49
Nonroad	3.98	3.01	3.25
Airplanes	3.91	4.50	2.49
Cement	0.80	0.80	0.80
Total	100.00	100.00	100.00
N (counties)	3108	1085	2023

Data source: [15]. Note: Excludes Alaska and Hawaii, which accounted for 0.01% of total U.S. emissions in 2002.

2.3. Independent Variables

The 2001 National Land Cover Dataset (NLCD) [81] was used to construct urban form measures. The NLCD employs a 16-class land cover classification scheme at applied to gridded 30-meter pixels. The four “developed” land use classes in the NLCD product were extracted to construct variables representing urban form (Table 3, Figure 2). For each county, total developed area is the sum in hectares of all four developed classes. To quantify differences in development intensities, a measure of high intensity developed land use was defined as follows:

$$\% \text{ dev., hi intensity} = ((\text{Area 23} + \text{Area 24})/(\text{Area 21} + \text{Area 22} + \text{Area 23} + \text{Area 24})) \times 100 \quad (5)$$

Table 3. Developed area classification types.

Classification Category	Description
Area 21: Developed, Open Space	Areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
Area 22: Developed, Low Intensity	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units.
Area 23: Developed, Medium Intensity	Areas with a mixture of constructed materials and vegetation. Impervious surface accounts for 50% to 79% of the total cover. These areas most commonly include single-family housing units.
Area 24: Developed, High Intensity	Highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses, and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover.

Source: [82].

Variables quantifying total developed area and proportional shares by intensity class represent spatial composition. Measures of spatial configuration (i.e., pattern) were not included in this study to ease interpretation, although future work can further investigate its effects.

The 2000 U.S. Census provides measures for total population, number of households, per capita and per household income, and fossil fuel use (Table 4). Data estimating reliance on fossil fuel sources for home heating were quantified as the percent of housing units heated by fossil fuel sources. Mean January temperature was quantified from the PRISM 4km gridded mean January temperature minimum for 2002 [83] by averaging pixel temperature values within each county. The fossil fuel and January temperature variables were used only for STIRPAT models of residential emissions given the

expected importance for their effects in that sector. January temperature is assumed to represent home heating demand. Home cooling demand during the summer, as might be indicated by a mean summer month temperature, is excluded because home cooling is largely produced by the electricity sector not included in this analysis.

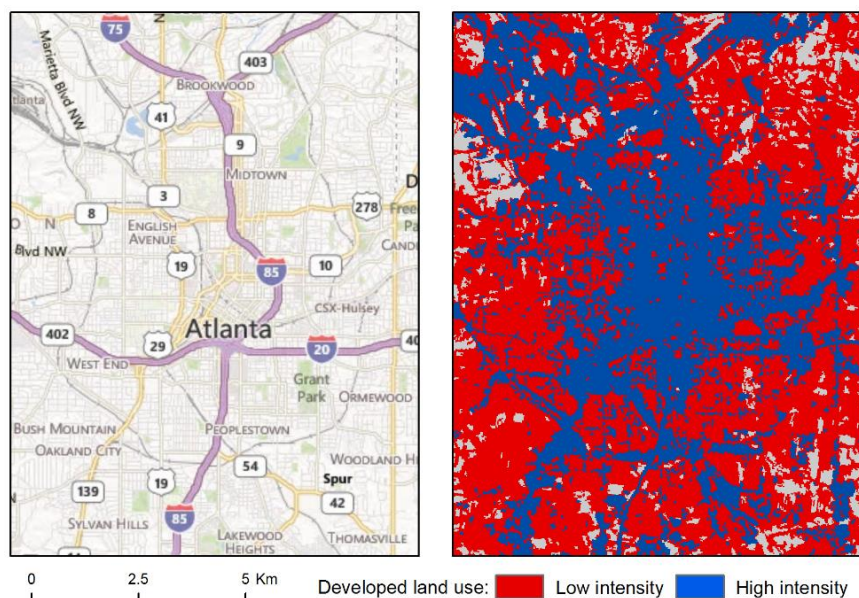


Figure 2. Developed land use in Atlanta, 2001.

Table 4. Definition of variables.

Variable	Description
CO ₂ on road emissions	On road CO ₂ emissions in tonnes, 2002
CO ₂ residential emissions	Residential CO ₂ emissions in tonnes, 2002
Population	Total population, 2000
Households	Number of households, 2000
Developed area	Hectares of developed land area, 2001
Pop. per developed area	Population per hectare of developed land area
Hhs per developed area	Households per hectare of developed area
% dev. high intensity	Percent of developed land area that is high intensity development
Per capita income	Income per population, 2000
Per hh income	Income per household, 2000
January temperature	Mean January minimum temperature in degrees Celsius
% hhs fossil fuel	Percent of housing units heated by fossil fuel sources, 2000

Population density was calculated as total population divided by total NLCD developed area, and is used in STIRPAT models of onroad emissions. Given that Vulcan's residential emissions are dominated by home space and water heating, a similar measure of household density is used in STIRPAT models of residential emissions. This approach using NLCD's area is important because a some or even much of a county's land area may not contain any population and may not even be developable (e.g., water bodies, steep terrain), and thus is an improved measure compared to simple population density using county area. A caveat is that not all population resides in areas classified as "developed" in the NLCD product due to classification error and the 30 m pixel resolution of NLCD. Additionally, not all developed areas are residential.

Descriptive statistics are shown in Table 5. Twelve preliminary ordinary least squares (OLS) regression models (not shown) were estimated prior to spatial regression models presented below. Variance inflation factors (VIF) and condition indices from the preliminary OLS models revealed that

multicollinearity was not a problem. The mean of the 12 models' mean VIFs was 1.79. The maximum VIF for an individual variable in all 12 models was 3.30.

Table 5. Descriptive statistics for variables analyzed.

	Metropolitan Counties				Non-Metropolitan Counties			
	Mean	SD	Min	Max	Mean	SD	Min	Max
CO ₂ onroad emissions ¹	0.28	0.52	0.00	9.36	0.04	0.04	0.00	0.36
CO ₂ residential emissions ¹	0.08	0.17	0.00	3.25	0.01	0.01	0.00	0.12
Population ²	213.1	47.2	1.8	9519.3	23.9	22.6	0.1	182.2
Households ²	79.5	167.3	0.7	3133.8	9.2	8.7	0.0	71.5
Developed area ³	21.4	26.1	0.2	351.9	9.0	5.0	0.3	45.7
Pop. per developed area	8.2	11.7	0.5	270.7	2.7	2.0	0.0	19.7
Hhs per developed area	3.1	5.0	0.2	130.1	1.0	0.8	0.0	8.0
% dev. high intensity	14.4	12.0	0.2	90.0	5.0	4.2	0.0	43.5
Per capita income ²	21.9	4.9	10.1	49.3	17.6	3.1	5.3	45.7
Per hh income ²	58.3	13.0	33.0	121.2	45.5	7.4	20.5	99.9
January temperature	6.6	6.6	−9.7	24.9	4.8	6.9	−11.4	24.7
% hhs fossil fuel	65.6	21.2	3.1	97.0	72.0	17.9	3.8	98.7
n	1085				2023			

Some minimum values reported as zero due to rounding. Units reported in: ¹ million tonnes, ² thousands, ³ thousand hectares.

2.4. STIRPAT Models

STIRPAT models were estimated separately for metro and non-metro counties and separately for onroad and residential emissions. Diagnostics identified the presence of positive spatial autocorrelation for residuals in all preliminary least squares models. The Lagrange multiplier decision rule [84] showed spatial error regression to be the appropriate functional form for all models. Spatial error regression is appropriate in situations with omitted variable bias due to model underspecification. These diagnostics confirmed expectations related to the likely clustering of omitted technology and other contextual variables as described previously. Spatial error regressions were specified as follows:

$$y = \alpha + \sum_k \beta_k x_k + \lambda W \varepsilon + u \quad (6)$$

where y is the dependent variable representing CO₂ emissions, x_k is a vector of independent variables, and β_k is a vector of coefficient parameter estimates, and ε represents the error residual from the original least squares regression. A weights matrix W was specified according to Queen's case contiguity so that counties sharing the focal county's border were defined as neighbors, and the spatial neighbor effects are reflected in the lambda coefficient parameter estimate λ . The remaining error is denoted by u . Parameters of spatial error regression are estimated using the maximum likelihood method.

3. Results

3.1. Onroad Emissions—Metropolitan Counties

The STIRPAT specification of Model 1 includes only population and per capita income as independent variables (Table 6). Model 1 is treated as a base model that is understood to be underspecified (as are later Models 4, 7, and 10). Population accounts for most of the variation as indicated by its large standardized coefficient (Beta). Population's raw coefficient is supralinear with $\beta < 1.0$. The effect of income is positive and significant in all Models 1–3, but the magnitude doubles in size for the more fully specified Models 2 and 3.

Table 6. Spatial error regression of CO₂ onroad emissions (natural log) for metropolitan counties.

Independent Variables	Model 1			Model 2			Model 3					
	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta			
Population (log)	0.854	***	±0.017	0.954	0.975	***	±0.022	1.089				
Developed area (log)									0.975	***	±0.022	0.779
Pop. per developed area (log)					−0.248	***	±0.049	−0.146	0.727	***	±0.045	0.428
% dev., high intensity					−0.006	***	±0.003	−0.057	−0.006	***	±0.003	−0.057
Per capita income (log)	0.135	*	±0.115	0.023	0.266	***	±0.108	0.046	0.266	***	±0.108	0.046
Lambda	0.209	***	±0.065		0.216	***	±0.065		0.216	***	±0.065	
Constant	0.773				−1.371	**			−1.371	**		
Pseudo R2	0.925				0.938				0.938			
n	1085				1085				1085			

Beta is standardized coefficient; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; 95% confidence interval = $\pm 1.96 \times \text{S.E.}$

Models 2 and 3 introduce additional variables to evaluate the effects of urban form. Population's effect in Model 2 is substantially larger than the effect in Model 1, yet is still supralinear. Both Models 2 and 3 use population density and % high intensity development. Model 2 includes the population variable. Model 3 replaces population with the developed area variable. This strategy of differently specified models, alternately using population versus developed area throughout, permits a more nuanced interpretation of the effects of population, developed area, and density.

Results for density differ (Pop. per developed area) for Models 2 and 3. The negative effect in Model 2 indicates that, if other variables are held fixed, higher density is associated with lower onroad emissions. Because population is a variable being held fixed, a reduction in developed area is associated with lower emissions and vice versa. In Model 3, the sign for density is positive, which is initially counterintuitive given Model 2's negative sign. By using developed area instead of population in Model 3, the interpretation is that, holding developed area and other variables fixed, an increase in population is associated with higher emissions and vice versa. The different signs for density in Models 2 and 3 are consistent with each other and show via different model specifications the influences of both population and developed land area. While increases in both population and developed area are associated with higher emissions as indicated by these two different models, both effects are supralinear with $\beta < 1.0$.

Results for % high intensity are consistent across Models 2 and 3 and are highly significant. The inclusion of developed area and % high intensity derived from NLCD's remote sensing classification is an innovation that enables one to evaluate the role of total developed land use as well as the proportional share of different intensity classes. The negative sign for % high intensity is an important result suggesting that, holding total developed area and other variables fixed, shifting some of the low intensity land to high intensity use is associated with lower emissions.

3.2. Onroad Emissions—Non-Metropolitan Counties

Results for non-metropolitan onroad emissions show similarities with the metropolitan results and some key differences (Table 7). Per capita income is not significant in any of the non-metro models, whereas it had a positive effect in all metro models. Population in Model 4, again treated as an underspecified base model, is supralinear and similar to that in Model 1. Its effect increases in Model 5, but is still supralinear. In Models 5 and 6, the effects of density, population, and developed land area have the same signs, similar magnitudes, and identical interpretations as the prior metro models. The most important difference is the significantly positive effect for % high intensity in Models 5 and 6. Unlike metro counties, there is no advantage in terms of carbon reduction to having a higher proportion of high intensity relative to low intensity land use. In fact, results suggest that higher proportions of high intensity use are disadvantageous for non-metro counties.

Table 7. Spatial error regression of CO₂ onroad emissions (natural log) for non-metropolitan counties.

Independent Variables	Model 4			Model 5			Model 6					
	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta			
Population (log)	0.834	***	±0.021	0.826	0.955	***	±0.034	1.003				
Developed area (log)								0.955	***	±0.034	0.606	
Pop. per developed area (log)					−0.253	***	±0.050	−0.214	0.702	***	±0.035	0.595
% dev., high intensity					0.010	**	±0.006	0.044	0.010	**	±0.006	0.044
Per capita income (log)	0.050		±0.125	0.009	0.069		±0.128	0.012	0.069		±0.128	0.012
Lambda	0.302	***	±0.054		0.386	***	±0.051		0.386	***	±0.051	
Constant	1.782	***			0.554				0.554			
Pseudo R2	0.802				0.813				0.813			
n	2023				2023				2023			

Beta is standardized coefficient; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; 95% Confidence interval = $\pm 1.96 \times \text{S.E.}$

3.3. Residential Emissions—Metropolitan Counties

For metropolitan residential emissions, the effect of household count in Models 7 and 8 (Table 8) is not significantly different from 1.0, indicating a linear scaling relationship. Per household income is not significant in Models 7–9. Control variables for levels of fossil fuel use and mean January temperature have expected signs, similar magnitudes, and are highly statistically significant in Models 7–9.

Table 8. Spatial error regression of CO₂ residential emissions (natural log) for metropolitan counties.

Independent Variables	Model 7			Model 8			Model 9					
	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta			
Households (log)	1.103	***	±0.015	0.887	0.996	***	±0.023	0.872				
Developed area (log)								0.996	***	±0.023	0.662	
Hhs per developed area (log)					0.109	***	±0.053	0.051	1.105	***	±0.046	0.514
% dev., high intensity					−0.004	***	±0.003	−0.034	−0.004	**	±0.003	−0.034
Per hh income (log)	0.082		±0.012	0.011	0.047		±0.113	0.006	0.047		±0.113	0.006
January temperature	−0.044	***	±0.006	−0.191	−0.043	***	±0.006	−0.185	−0.043	***	±0.006	−0.185
% hhs fossil fuel	0.016	***	±0.002	0.225	0.017	***	±0.002	0.235	0.017	***	±0.002	0.235
Lambda	0.518	***	±0.049		0.500	***	±0.050		0.500	***	±0.050	
Constant	−2.087	***			−1.614	***			−1.614	**		
Pseudo R2	0.956				0.966				0.965			
n	1085				1085				1085			

Beta is standardized coefficient; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; 95% confidence interval = $\pm 1.96 \times \text{S.E.}$

Density in Models 8 and 9 is represented as households per developed area. Parameter estimates are positive and significant. These results are seemingly contradictory given the results showing opposite signs for density in the prior models for onroad emissions. Consideration of the differing model specifications provides a consistent and logical interpretation. The positive effect for density in Model 8 indicates that, holding other variables fixed, higher household density is associated with higher residential emissions. Given that the number of households is a variable being held fixed, a reduction in developed area is associated with higher residential emissions and vice versa. Why would this be the case? Higher amounts of developed land area are associated with the urban heat island effect that raises temperatures. Conversely, lower amounts of developed area act to reduce temperature due to a less impervious surface, leading to greater energy use and carbon emissions for home heating during the cold season. The positive effect for density in Model 9 indicates that, holding developed area and other variables fixed, an increase in households is associated with higher residential emissions and vice versa. This is simply reflecting the population effect, with households being generally equivalent to population.

The negative effect for % high intensity in Models 8 and 9 is an important result showing that, holding total developed area and other variables fixed, shifting some of the low intensity developed land to high intensity use is associated with lower emissions. This is likely reflective of greater home heating efficiencies of higher intensity development associated with a greater prevalence of

multi-family and attached housing. These results for metro residential emissions and the prior results for metro onroad emissions suggest the positive benefits of a land use mix with a higher proportion of high intensity relative to low intensity land use in metro regions.

3.4. Residential Emissions—Non-Metropolitan Counties

For non-metropolitan residential emissions (Table 9), the effect of household count is superlinear with $\beta > 1.0$ (Models 10 and 11). A significantly positive income effect is consistent across Models 10–12, as are the effects for January temperature and fossil fuel usage, which are consistent with those in metro Models 7–9.

Table 9. Spatial error regression of CO₂ residential emissions (natural log) for non-metropolitan counties.

Independent Variables	Coeff.	Model 10			Model 11			Model 12				
		95% Conf.	Beta	Coeff.	95% Conf.	Beta	Coeff.	95% Conf.	Beta			
Households (log)	1.022	***	±0.018	0.894	1.042	***	±0.028	0.912				
Developed area (log)								1.042	***	±0.028	0.557	
Hhs per developed area (log)					−0.051	*	±0.045	−0.036	0.991	***	±0.033	0.701
% dev., high intensity					0.003		±0.005	0.009	0.003	***	±0.005	0.009
Per hh income (log)	0.172	**	±0.21	0.023	0.180	**	±0.123	0.024	0.180	**	±0.123	0.024
January temperature	−0.038	***	±0.003	−0.228	0.037	***	±0.006	−0.223	−0.037	***	±0.006	−0.223
% hhs fossil fuel	0.017	***	±0.002	0.264	0.017	***	±0.002	0.262	0.017	***	±0.002	0.262
Lambda	0.643	***	±0.037		0.647	***	±0.038		0.647	***	±0.037	
Constant	−3.229	***			−3.521	***			−3.521	***		
Pseudo R2	0.925				0.925				0.925			
n	2023				2023				2023			

Beta is standardized coefficient; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; 95% confidence interval = $\pm 1.96 \times \text{S.E.}$

Parameter estimates for household density are highly significant yet have opposite signs in Models 11 and 12. The finding of opposite signs for density is identical to results found for onroad emissions (both metro and non-metro), but differs from results for metro residential emissions (Models 8 and 9) where the signs were both positive and interpretable via the urban heat island effect. In Model 11, the negative sign for household density indicates that, holding other variables fixed, higher density is associated with lower residential emissions. Given that the number of households is a variable being held fixed, a reduction in developed area is associated with lower emissions and vice versa. For these non-metro counties, the urban heat island effect that might lower cold season temperatures with reduced amounts of developed area is likely to be negligible if present at all. This negates the need for increased energy use for home heating. A logical interpretation is that lower amounts of developed area requires less energy use for home heating, an interpretation consistent with the positive superlinear effect for developed area in Model 12. The positive effect for density in Model 12 indicates that, holding developed area and other variables fixed, an increase in households is associated with higher residential emissions and vice versa. As before, this is simply reflecting the household effect (and related population effect) where introducing more households (population) requires more energy use and emissions for home heating.

Unlike all previous models, results for % high intensity in Models 11 and 12 were not significant. This suggests no evidence for advantages or disadvantages of higher proportions of high intensity land use in non-metro counties regarding residential emissions.

4. Discussion

This research theorized urban form as a technological driver of CO₂ emissions within the STIRPAT framework and draws from the field of science and technology studies. Urban form is a manifestation of artifacts, practices, and knowledge that are part of a broader socio-technical system with important connections to CO₂ emissions. Empirically, results demonstrated that urban form does matter in several, but not all, cases for onroad and residential emissions, and with varying importance depending on sector and metro versus non-metro settings.

Twelve spatial error regression models were estimated using different specifications. Table 10 summarizes results for selected variables most germane to discussion and excludes the “base models” 1 and 7. Results from only those models introducing developed area and % high intensity into the STIRPAT framework are summarized in due to the theoretical and empirical interest in the role of urban form.

Table 10. Summary of effects for selected models and variables.

	Metro CO ₂ Onroad Emissions		Non-Metro CO ₂ Onroad Emissions	
	Model 2	Model 3	Model 5	Model 6
Population (log)	$\beta < 1.0$, supralinear		$\beta < 1.0$, supralinear	
Developed area (log)		$\beta < 1.0$, supralinear		$\beta < 1.0$, supralinear
Pop. per dev area (log)	Negative effect	Positive effect	Negative effect	Positive effect
% dev., high intensity	Negative effect	Negative effect	Positive effect	Positive effect
	Metro CO ₂ Residential Emissions		Non-Metro CO ₂ Residential Emissions	
	Model 8	Model 9	Model 11	Model 12
Households (log)	$\beta = 1.0$, linear		$\beta > 1.0$, superlinear	
Developed area (log)		$\beta = 1.0$, linear		$\beta > 1.0$, superlinear
Hhs per dev area (log)	Positive effect	Positive effect	Negative effect	Positive effect
% dev., high intensity	Negative effect	Negative effect	Not significant	Not significant

For onroad emissions, the effects of population and developed area are supralinear for both metro and non-metro counties. Results for metro counties show that having more high intensity developed development reduces emissions. However, there is an opposite effect of non-metro counties, which merits further investigation. Given that metro counties produce a large majority of emissions, the net effect of high intensity developed is beneficial in terms of reducing emissions. The pattern of alternating negative and positive effects of density (Pop. per dev area) are seemingly counterintuitive, but are explained by the alternate use of population and developed area in the models as described previously and show that reductions in population or developed land use reduces emissions.

For residential emissions, the effects of population and developed area are linear ($\beta = 1.0$) for metro counties and superlinear ($\beta > 1.0$) for non-metro counties. From a carbon reduction standpoint, this is an unwelcome finding that, although this finding is tempered by the fact that residential emissions account for a much lower percentage of total emissions. Results for metro counties show that having more high intensity developed development reduces residential emissions, a finding consistent with metro onroad emissions that points to benefits of higher intensity land use. High intensity land use had no effect for non-metro counties. Positive effects for density in metro models are explained by the urban heat island effect as described previously and do not negate the interpretation of carbon reduction benefits of high intensity development. They simply reflect the reality that more population necessarily entails more emissions.

Where income is statistically significant, its effect is positive, which conforms to expectations; however, it is interesting that income is not significant for metro residential and non-metro onroad emissions. It would be desirable in all models to have included variables measuring the price of gasoline and home heating fuel. It is possible that specifying these price variables or suitable proxies could alter income effects.

Positive population and income effects arguably present challenges for policy strategies with respect to total emissions, where a focus is on total emissions rather than per capita emissions. While reduction in U.S. per capita emissions following 2007 [80] is desirable and commendable, focusing on total emissions is the paramount concern because climate change responds to total emissions in the Earth’s atmosphere. Policymakers promote strategies to enhance economic growth. Depending on local contexts, they may desire slow or accelerated growth in terms of population, but in most cases desire strong growth in income. IPAT-related research shows that population and income growth are positively associated with emissions. Focusing on these two levers of population size and income level would seem to limit policies for CO₂ emissions reduction options to either a no growth or slow growth

agenda; or, even a degrowth agenda. Shifting attention to other mitigation strategies offers a more expanded set of policy options. Behavioral modification (e.g., lowered household consumption) and clean technology development are two such strategies with obvious potential and advances in recent years. However, they entail difficulties related to challenges in behavior modification and the time horizons associated with transition to cleaner energy sources.

Results presented here point to urban form as a driver of emissions and suggest the need for heightened attention to land use as a carbon mitigation strategy. Attention to urban form has clear connections to the Smart Growth paradigm, where sensitivity to urban form and densification underpins a goal of promoting sustainable growth [85–87]. Urban form is a sociotechnical system producing built environments that has implications for CO₂ emissions. Stronger consideration of developed land use patterns has the potential to give actors in this sociotechnical system greater leverage to enact mitigation strategies, though it also comes with challenges of behavior modification and required public will since it requires reducing consumption—reduced consumption of developed land use. The various STIRPAT models were specified in novel ways precisely to identify such leverage points.

An innovation of this research is the introduction of high intensity developed land use to STIRPAT specifications as a measure of urban form where total developed area was decomposed into the proportional shares of high versus low intensity development. Both population density and household density are not altered by changes in this variable since total developed area remains the same. The effects of high intensity share are particularly notable for metro emissions where a greater share in high intensity reduces both onroad and residential emissions. The mean share of total developed area was 14.4% high intensity and 85.6% low intensity for metro counties. In a “what if” scenario for metro counties, how much would emissions have been different in an average metro county if proportions were shifted five percentage points to 19.4% high intensity and 81.6% low intensity? Using parameter estimates and standard errors from metropolitan regression models described earlier (specifically Models 3 and 9), CO₂ reductions obtained by increasing the high intensity share five percentage points (and corresponding decrease in low intensity share) range from 4.76 to 4.99 percent (here not percentage points) for residential emissions and 1.53 to 4.18 percent for onroad emissions (Table 11). Proportional shifts of land use like this imply shifts of some of population from areas classified as low intensity use into an expanded high intensity class while total developed area and total population remains constant. At some threshold of greater proportional shift of these land classes, this interpretation becomes untenable, so that it is only appropriate to perform this exercise for relatively small shifts. Note though that a greater proportion of high intensity developed land use might require less total developed area, which would be beneficial for carbon reduction.

Table 11. Ninety-five percent confidence bounds for percent reduction in CO₂ emissions in 2002 applying a five-percentage point shift in the proportion of developed land area from low intensity to high intensity use.

	95% Lower	Middle	95% Upper
Residential—metro	4.76%	4.87%	4.99%
Residential—nonmetro	na	na	na
Onroad—metro	1.53%	2.86%	4.18%
Onroad—nonmetro	na	na	na

na = five percentage point increase not applied due to no carbon reduction benefits.

The cross-sectional and historical nature of the data used invite a desire for more current and multi-temporal analyses. Further, and within the bigger picture of total CO₂ emissions across all sectors, the magnitude of effects is modest, but statistically significant as suggested by the “what if” scenario. Similar to land change science, which has matured to examine patterns and drivers of land cover change across richer time depth, there is a need for studies to more explicitly link marginal land use changes to changes in carbon emissions. Other limitations include data uncertainties in the

Vulcan emission estimates [88,89] and the NLCD land cover product [82]. Finally, it is desirable to more fully specify models to include indicators of price variability of energy costs and other important contextual variables.

5. Conclusions

The human impact on the Earth's changing climate is now well established within the science community, and requires research and policy responses to mitigate future greenhouse gas emissions and develop adaptive strategies that promote human well-being in the face of future climate regimes [1]. By focusing on drivers of CO₂ emissions, this research speaks to the need for strategies focusing on urban form. This theoretical and analytical approach is representative of a research agenda that integrates GIScience and energy research [29]. In doing so, it incorporates paradigms from land change science [90] and structural human ecology [10] in novel ways. Empirical results confirm that urban form matters. However, urban form matters differently in terms of sign, significance, and interpretation depending on emission sector and metro versus non-metro status. Much of the prior STIRPAT analyses operate at coarse national scales. Scales such as the county or finer are important because they are situated at the place-based scales at which land use mitigation policy might be implemented for maximum effect. Methodologically, the strategy of multiple model specification involving alternate specification using population/households versus developed area enabled more nuanced interpretation of the effects of developed area, density, and the likely influence of the urban heat island effect with respect to developed area coverage. Spatial error regression was demonstrated to be an appropriate functional form confirming expectations related to spatial clustering of unobserved technology and other contextual variables.

Treating urban form as both product and process of a sociotechnical system opens possibilities for future studies to investigate in greater depth the various actors, artifacts, practices, and knowledge responsible for urban form that influences CO₂. Such work will require mixed methodologies involving both quantitative and qualitative paradigms, multi-scale and place-based studies, and analytical strategies that might include, but are not limited to, the STIRPAT framework. Finally, results showing that urban form matters must be tempered by the recognition of its modest quantitative effects compared to the much larger effects made possible by transition to cleaner energy sources and less consumptive human behaviors.

Author Contributions: Conceptualization, T.W.C.; data curation, T.W.C.; methodology, T.W.C.; validation, T.W.C.; formal analysis, T.W.C.; writing—original draft preparation, T.W.C.; writing—review and editing, T.W.C.; visualization, T.W.C. The author has read and agreed to the published version of the manuscript.

Funding: The author received a US–UK Fulbright Commission, Fulbright Scholar Award that supported this research.

Acknowledgments: Thank you to David Green, Department of Geography and Environment, University of Aberdeen for his generosity and support in providing research space, resources, and collegiality.

Conflicts of Interest: The authors declare no conflict of interest.

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