

Urban high-resolution fossil fuel CO₂ emissions quantification and exploration of emission drivers for potential policy applications

Risa Patarasuk¹ · Kevin Robert Gurney^{1,2} ·
Darragh O’Keeffe^{1,2} · Yang Song¹ · Jianhua Huang¹ ·
Preeti Rao³ · Martin Buchert⁴ · John C. Lin⁵ ·
Daniel Mendoza⁵ · James R. Ehleringer⁶

© Springer Science+Business Media New York 2016

Abstract Fossil fuel carbon dioxide (FFCO₂) emissions are the largest driver of anthropogenic climate change. Approximately three-quarters of the world’s fossil fuels carbon dioxide emissions are generated in urban areas. We used the Hestia high resolution approach to quantify FFCO₂ for Salt Lake County, Utah, USA and demonstrate the importance of high resolution quantification to urban emissions mitigation policymaking. We focus on the residential and onroad sectors across both urbanized and urbanizing parts of the valley. Stochastic Impact by Regression on Population, Affluence, and Technology (STIRPAT) regression models using sociodemographic data at the census block group level shows that population, per capita income, and building age exhibit positive relationships while household size shows a negative relationship with FFCO₂ emissions. Compact development shows little effect on FFCO₂ emissions in this domain. FFCO₂ emissions in high income block groups is

Electronic supplementary material The online version of this article (doi:10.1007/s11252-016-0553-1) contains supplementary material, which is available to authorized users.

✉ Risa Patarasuk
risa.patarasuk@asu.edu

¹ School of Life Sciences, Arizona State University, P.O. Box 874501, Tempe, AZ 85287, USA

² Global Institute of Sustainability, Arizona State University, P.O. Box 875502, Tempe, AZ 85287, USA

³ Jet Propulsion Laboratory, 4800 Oak Grove Drive, Pasadena, CA 91109, USA

⁴ Global Change and Sustainability Center, University of Utah, 155 South 1452 East, Salt Lake City, UT, USA

⁵ Department of Atmospheric Sciences, University of Utah, 135 South 1460 East, Salt Lake City, UT 84112, USA

⁶ Department of Biology, University of Utah, 257 South 1400 East, Salt Lake City, UT 84112, USA

twice as sensitive to income than low income block groups. Emissions are four times as sensitive to household size in low-income versus high-income block groups. These results suggest that policy options targeting personal responsibility or knowledge feedback loops may be the most effective strategies. Examples include utility bill performance comparison or publicly available energy maps identifying high-emitting areas. Within the onroad sector, high emissions density (FFCO₂/km) is associated with primary roads, while high emissions intensity (FFCO₂/VMT) is associated with secondary roads. Opportunities exist for alignment of public transportation extension with remaining high emission road segments, offering a prioritization of new onroad transportation policy in Salt Lake County.

Keywords Residential · Onroad · STIRPAT · Urban carbon · Hestia · Bottom-up approach

Introduction

Carbon dioxide emissions from the combustion of fossil fuels (FFCO₂) is the largest driver of anthropogenic climate change (Ciais et al. 2013). Climate change poses irreversible adverse environmental effects in different regions of the world (Solomon et al. 2009) including increases in global atmospheric and ocean temperatures (Petit et al. 1999; Shakun et al. 2012), changes in precipitation patterns (Trenberth 2011; Dai 2013), shrinking of ice sheets (Polyakov et al. 2010; Rignot et al. 2011), rising sea-level (Meehl et al. 2005; Rahmstorf 2007), and alteration of the carbon cycle (Cox et al. 2000; Schuur et al. 2008).

Though urban areas only cover about 3 % of the earth's land surface, more than 50 % of the world's population currently reside in urban areas and this figure is projected to increase to around 70 % by 2050 (Collins, et al. 2013). During the 1970–2000 time period, urban area extent grew by 58,000 km² and is projected to expand by 1.2 million km² by the year 2030 (Seto et al. 2011, 2012). Hence, approximately three-quarters of the world's energy-related FFCO₂ emissions are generated in the urban areas (IEA 2008; Seto et al. 2014) and these FFCO₂ emissions are projected to grow by 1.8 % per year in the near future (IEA 2009). Acknowledging these trends, many cities/local governments are seeking measures to reduce FFCO₂ emissions in urban areas (Kennedy et al. 2009; WWF and ICLEI 2015). However, in order to enable FFCO₂ emissions mitigation, reliable FFCO₂ emissions data products are critically needed. Having such data products, especially in high spatial-temporal resolution, will increase the understanding of the carbon cycle, particularly at an urban scale (Gurney et al. 2007; Kennedy et al. 2009; Turnbull et al. 2015). Most importantly, such data can guide targeted, efficient mitigation policy options for urban stakeholders.

Past efforts to build gridded FFCO₂ emissions data products have been driven by both scientific and policy-related questions. The scientific need has been mostly associated with atmospheric CO₂ inversions which are used to better understand the global carbon cycle and the feedbacks between the carbon cycle and climate change (Gurney et al. 2002; Stephens et al. 2007; Lauvaux et al. 2009, 2016). Inversions use measurements of atmospheric CO₂ concentration combined with models of atmospheric transport to estimate carbon exchange with the land and oceans. Because of the limited observational constraint on many components of the carbon cycle, this approach requires a prior estimate of the FFCO₂ emissions in order to solve for the carbon uptake in the terrestrial biosphere and oceans. Traditionally tackled at the global scale, these efforts have relied upon global, gridded FFCO₂ emissions data products

constructed using a variety of techniques but most often using fossil fuel production/consumption statistics and spatial proxies such as population or remotely sensed nighttime lighting (Rayner et al. 2010; Wang et al. 2013; Asefi-Najafabady et al. 2014).

The policy-related need, by contrast, has been driven by the increasing need to verify anthropogenic mitigation efforts associated with policy agreements. This verification capability must be independent of political or regulatory influence. The need was best summarized in a 2010 National Academy of Sciences report where assessment of current scientific verification capabilities was reviewed and the need for building a future verification system were described (NRC 2010). As with the scientific motivation, the generation of gridded FFCO₂ estimates was viewed by the authors as a critical element of a system driven principally by atmospheric monitoring combined with modeling atmospheric transport. Furthermore, the domain of such a system emphasized the need for such products at the nation-state to global scale, the primary policymaking arena over the last 30 years (Olivier et al. 2014; Asefi-Najafabady et al. 2014; UNFCCC 2015).

However, progress on climate change policy at the international level has moved slowly in the last decade. This has stimulated policymaking activity at scales below the nation state, best exemplified by a series of “non-state actors” including provinces, cities, NGOs and individual businesses (Hsu et al. 2015). As with the effort to generate gridded global FFCO₂ emission data products, a need has arisen to quantify and verify FFCO₂ emissions at sub-national scales using scientifically-based, independent techniques. Similarly, there is scientific interest in closing carbon budgets at smaller scales where the complications associated with biosphere or ocean carbon exchange are minimized and the source function of CO₂ emissions is far simpler. For policy-related interests, focus on smaller domains scales offers a more tractable domain to test verification systems.

Considerable progress has been made on the construction and analysis of monitoring and verification of FFCO₂ in urban domains. Work is ongoing in Indianapolis, IN (Gurney et al. 2012) via the INFLUX experiment (The Indianapolis Flux Experiment) (Turnbull et al. 2015; Lauvaux et al. 2016), Boston, MA (Gately et al. 2015), Salt Lake City, UT, the Los Angeles Basin, CA (Rao et al. 2016) and Paris, France (Bréon et al. 2015) with plans emerging for cities in Australia, China, and Brazil. In all of these domains the primary methodological approach is to monitor atmospheric CO₂ (via ground, aircraft and now satellite sensing) combined with gridded FFCO₂ emissions data products to best quantify FFCO₂ emissions and attribute sources in both space and time within the urban domain. In contrast to the techniques at the global scale, the techniques used to construct gridded FFCO₂ emissions are fully driven by a “bottom-up” approach which uses direct estimates of fuel consumption or fuel-consuming activity to generate FFCO₂ emissions, tied to specific geography and time.

One of the first examples of this approach was the Vulcan Project (Gurney et al. 2009). The Vulcan Project quantifies FFCO₂ emissions across the US landscape at sub-county spatial scales with an hourly time step for an entire year. The estimation provides not only flux estimation but functional information such as economic sector, fuel, combustion device, road class, etc. Originally built for a single calendar year (2002), work is underway to generate a multiyear time series and maintain progressive updates with time. Similar efforts have now been completed in other countries (Zhao et al. 2012; Wang et al. 2013) and for individual sectors (Gately et al. 2015).

To meet the policy and scientific interest in the urban domain, bottom-up estimation is now occurring within specific cities, resolving FFCO₂ emissions at the scale of individual buildings and streets (Gurney et al. 2012). Principal among these efforts is the Hestia Project which has

now completed bottom-up flux estimation efforts in the cities of Indianapolis (Zhou and Gurney 2010; Gurney et al. 2012), Salt Lake City, and the Los Angeles Basin (Rao et al. 2016) with work underway in Baltimore, MD. The use of the Hestia FFCO₂ emissions data product in the INFLUX experiment has demonstrated the potential to move beyond the simple prior flux – inversion approach to a more integrated effort that combines the best aspects of the inverse approach with the bottom up estimation (Lauvaux et al. 2016). The atmospheric CO₂ inversion approach relies upon very accurate CO₂ concentration observations (including ¹⁴CO₂) with strong potential to constrain the trends of emissions for the scale of an urban dome. However, the ability of the inversion approach to attribute emissions to particular economic sectors of activities remains challenging. The bottom-up estimation by contrast relies on a series of uncertain datasets in the absolute sense, but has high information content on attribution and functional detail. Integration of these two approaches offers both accurate large-scale constraints and highly resolved attribution information.

Useful for verification, this flux estimation approach can fulfill a more immediate need expressed by urban stakeholders. Many cities have set targets (mostly aspirational) for reducing greenhouse gas emissions (Wheeler 2008). Some cities generate carbon “footprints” – quantification of greenhouse gas emissions occurring within their city or chosen urban domain (Salt Lake City 2010; WWF and ICLEI 2015). These rarely go beyond a sectoral breakdown of emission totals and are often isolated to operations associated with city government rather than the complete emitting urban landscape. Though an important start for most cities, these zero-dimensional inventories offer little information content to design policy interventions or programs. The bottom-up emissions data products generated by the scientific community may offer far more information useful for policymaking and stakeholder engagement.

In this study, we demonstrate the utility of the scientific bottom-up FFCO₂ emissions estimation approach for answering the needs of urban decision makers charged with greenhouse gas emissions mitigation. We use Salt Lake City and County as our study domain and identify the drivers of FFCO₂ emissions in the residential sector and analyze the onroad transportation sector for acute emissions and coherent spatial patterns. Our study aims to answer the following questions: 1) What is the spatial structure of onroad transportation and residential FFCO₂ emission in Salt Lake County? 2) What factors drive FFCO₂ emissions in Salt Lake County? 3) Are there differences between the City versus the County? 4) How can the bottom-up quantification and driver analysis be used to aid public policy-decision making aimed at alleviating greenhouse emissions?

Our paper outline is as follows: a methods description identifies our study domain, describes the flux estimation procedure and the analysis methods used to deconstruct emissions; a results section which presents the detailed emissions, emission drivers, and spatial/hotspot identification; a discussion section which places this information within the context of policymaking for greenhouse gas mitigation; a conclusions section which summarizes our results, recommendations and identifies caveats and areas of future research.

Methods

The geographical domain of this study is Salt Lake County, Utah in the intermountain region of the western United States. Salt Lake City is the capital and the largest city in Utah. While it is also the county seat of Salt Lake County, the county is

home to several other cities (e.g., West Valley City, Murray, South Jordan, and Draper) which contribute the vast majority of the county population. The population in 2010 was 186,440 for Salt Lake City and 1,029,655 for Salt Lake County. The county represents over one-third of the state population of 2,763,885 (US Census Bureau 2015).

A few important attributes of Salt Lake City and County make it a strategic choice in which to apply the Hestia FFCO₂ quantification system. For one thing, the domain is the home of a long-term publicly available dataset of urban atmospheric CO₂ concentration measurements (<http://co2.utah.edu/>) (Pataki et al. 2006, 2007; Ehleringer et al. 2008, 2009; Strong et al. 2011; McKain et al. 2012). These measurements, in isolation or combined with atmospheric transport modeling, can be used to close the urban carbon budget from both the top-down and bottom-up, a key element in urban-scale MRV. Furthermore, the Salt Lake City metropolitan area has experienced rapid urbanization in the last 25 years, with an increase in population and urban expansion (Pataki et al. 2009; Salt Lake City 2011, 2014). Hence, granular quantification of FFCO₂ emissions can assist with the incorporation of climate policy into urban and regional planning. Salt Lake City has generated an action plan, called “Salt Lake City Green: Energy and transportation Sustainability Plan 2011”, which aims to reduce greenhouse emissions to 17 % below 2005 levels by 2020 (excluding air travel) (Salt Lake City 2011).

FFCO₂ estimation

The Hestia results presented here quantify FFCO₂ emissions for the entire Salt Lake County in eight sectors including airports, residential buildings, commercial (buildings and point sources), electricity production, industrial sources, non-road, onroad, and railroad. FFCO₂ emissions in the electricity production sector reflect emissions associated with electricity production facilities within the Salt Lake County domain regardless of where the electricity is consumed.

The methods used to quantify FFCO₂ emissions in Salt Lake County follow the general Hestia methodology described elsewhere (Zhou and Gurney 2010; Gurney et al. 2012). However, some methods were altered to accommodate specific circumstances associated with the data or domain in Salt Lake County, as described below.

A greenhouse gas footprint study performed by the city of Salt Lake provides a potential point of comparison to the work described here (Salt Lake City 2010). The “Salt Lake City: Community Carbon Footprint (SLCCCF)” includes a baseline estimate of 2009 CO₂-equivalent emissions for the Salt Lake City. Emissions estimates from the residential (~0.13 MtC), nonroad (~0.02 MtC), and airport (~0.09 MtC) sectors are consistent with the results found here, allowing for the fact that the two estimates represent two different calendar years (2009 versus 2011). The onroad sector emissions estimated here (0.32 MtC/yr) are about 50 % higher than the SLCCCF estimate (0.19 MtC/yr). This large difference could be due to the different approach taken in the emissions estimations; the SLCCCF uses a travel demand model versus the activity-based approach here. They also include greenhouse gases other than CO₂ and the difference in calendar 2009 versus 2011 may represent different economic conditions due to the Global Financial Crisis (GFC).

Commercial and residential building emissions

FFCO₂ emissions for the non-point commercial and residential sectors reflect the on-site combustion of fossil fuels. ‘Non-point’ sources refer to the emissions which are too small in magnitude individually or too many to inventory as individual point sources (EPA 2016). Emissions associated with the consumption of electricity in buildings are located at the electricity production facilities (point sources). Non-point building FFCO₂ emissions are quantified based on parcel data provided by the Salt Lake County Assessor’s Office. These parcel data are categorized into 11 commercial and 4 residential building types and further categorized into two vintages (post-1979 and pre-1980), yielding a total of 22 commercial and 8 residential building types. Nonelectric energy-use intensity (NE-EUI) for each building type is constructed using regional data supplied by the Commercial Building Energy Consumption Survey (CBECS) and the Residential Energy Consumption Survey (RECS) as well as a building energy model (eQUEST). The NE-EUI values are combined with the total floor area for each building in the parcel data to get the estimates of nonelectric energy consumption. However, these estimates were not used in the absolute form. They were used as a relative weighting among the residential and commercial buildings to the county total FFCO₂ emissions in the residential and commercial sectors, respectively. The county totals were retrieved from the Vulcan data product, which quantifies FFCO₂ emissions across the entire United States down to ~10 km (Gurney et al. 2009). Since the Vulcan estimates were based on the year 2002, county total FFCO₂ emissions were scaled to 2011 using state-level fuel statistics supplied by the Department of Energy’s Energy Information Administration (EIA 2013a). The parcel data was similarly updated to reflect the presence of buildings built up to, and including, the year 2011 (Salt Lake County Assessor’s Office 2013).

Mobile emissions

Mobile emissions include onroad, non-road, airport, and railroad sectors. Onroad FFCO₂ emissions are retrieved from the NEI 2011 estimates which provide FFCO₂ emissions in each US county according to 12 road types and 8 vehicle classes (EPA 2016). The 2012 Federal Highway Administration’s (FHWA) Highway Performance Monitoring System (HPMS) AADT (Annual Average Daily Traffic) data set was used to distribute the county total emissions onto a map of roads with distribution along roadways apportioned according to the segment’s fraction of total VMT within a road class (Salt Lake City Transportation Division 2013; Federal Highway Administration 2014). The VMT values, in turn, were calculated as the product of the AADT and road segment length. Crosswalk relationships between the road typology of the HPMS (7 types), the NEI (12 types), and the Hestia road type classification (3 types) are presented in Table 1.

Local roads presented an exception to the spatial distribution procedure, as the AADT data was extremely limited on these road types. In this instance, the US Census Bureau 2009 TIGER (Topologically Integrated Geographic Encoding and Referencing) base map was used and the total local road FFCO₂ emissions evenly distributed onto the local roads. Then the local road type base map surface was defined. This was considered an acceptable approximation given that local roads account for 22 % of the total onroad FFCO₂ emissions in Salt Lake County.

Distribution of onroad FFCO₂ emissions in time was based on the traffic count data which came from two difference sources. Traffic count data within the Salt Lake City domain was

Table 1 Hestia SLC road classification and relationship to Highway Performance Monitoring System (HPMS) road types

Hestia SLC road types	HPMS road types	NEI 2011 road types
Primary	Interstate, Freeways and Expressways, Other Principal Arterials	Rural Interstate, Urban Interstate, Rural Principal Arterial, Urban Principal Arterial, Urban Other Principal Arterial
Secondary	Minor Arterials, Major Collectors	Rural Minor Arterial, Urban Minor Arterial, Rural Major Collector, Rural Minor Collector
Local	Minor Collectors, Local Roads	Urban Collector, Rural Local, Urban Local

acquired for 1255 individual monitoring locations (Salt Lake City Transportation Division 2013). Each location was measured for a period of 7–10 days during the weekdays from 1999 to 2012. These measurements were then aggregated into a mean 24 hour cycle. Additional data were retrieved from the 17 FHWA's (Federal Highway Administration) ATR (automatic traffic recorder) monitoring stations located throughout the county (Federal Highway Administration 2014). These stations contain hourly data for the entire year and were collected during 2007–2008.

In order to assign all road segments with an hourly time structure, the hourly traffic count data within the Salt Lake City domain were kriged. This was done for weekdays only because there is no data available for the weekends. The weekend temporal structure follows the ATR station measurements. The 24-h temporal structure for the rest of the Salt Lake County was derived from the 17 ATR stations using a theissen polygon approach (see Gurney et al. 2009).

The “non-road” sector refers to mobile sources that do not travel on roads such as snowmobiles, lawnmowers, farm tractors, and construction tractors. The FFCO₂ emissions data are obtained from the NEI 2011 and the data is reported at the county scale. No further downscaling is attempted in the Hestia data product.

There are two airports in the Salt Lake County: Salt Lake International Airport (SLC) and South Valley Regional Airport (U42). FFCO₂ emissions for these airports are based on the 2002 Vulcan estimates scaled to the year 2011 using scaling factors based on state-level fuel sales specific to aircraft (EIA 2013b). Airport emissions reflect the consumption of fuel in aircraft during the taxi, takeoff, and landing (below 3000 ft) activity cycles. Emissions associated with all other airport activity are captured in building or non-road emitting categories. The sub-annual time structure associated with the airport emissions was derived takeoff/landing statistics supplied by AirNav (<https://www.airnav.com/>) (AirNav 2014) and personal communication with Los Angeles World Airports (LAWA).

Railroad FFCO₂ emissions reflect that portion of state-level railroad emissions within the county boundary. The state-level emissions are derived from fuel sales into the railroad sector combined with a distillate oil CO₂ emission factor and a railroad GIS atlas (EIA 2002; RITA 2012). Spatial distribution along the rail lines are derived from freight tonnage statistics (RITA 2012). A scaling factor is also used to estimate the 2011 railroad FFCO₂ emissions.

Point source emissions

FFCO₂ emissions for the commercial and industrial sector point sources are based on the Vulcan estimates, which originally obtained from the NEI CO point-source pollution reporting

in 2002. A scaling factor is also used to arrive at the 2011 FFCO₂ estimates. There are 51 and 140 point sources reported as emitting points in the commercial and industrial sectors respectively. Together, these point sources constitute 74 individual locations, as most facilities report several emission points but report them as a single location (i.e., by latitude and longitude). Visual inspection via Google Map and re-geocoding for some locations were necessary to ensure the accuracy of the point locations.

The electricity production emissions reporting data are obtained from three different sources: the US Environmental Protection Agency (EPA) Clean Air Market Division (CAMD), the US Energy Information Administration (EIA), and the US EPA's NEI. Two facilities in Salt Lake County report to the CAMD, five to the EIA, and 14 to the NEI. These locations were also geocoded and verified. The corrections in terms of the locations were made where necessary. FFCO₂ emissions are reported every year; thus, no scaling factor is applied.

FFCO₂ drivers – regression analysis

Factors that may contribute to variations in urban FFCO₂ emissions include, but are not limited to, socio-demography (e.g. population, income, age, household size, education), urban form, population and housing density, geographic location, transportation network, and buildings characteristics (e.g. size, type, age) (Newman and Kenworthy 1989; Ewing and Rong 2008; Glaeser and Kahn 2010; Zheng et al. 2010; Dodman 2011). Studies such as Cole and Neumayer (2004) and Poumanyvong and Kaneko (2010) have shown a relationship between FFCO₂ emissions and population in which FFCO₂ emissions increase with population. Increases in per capita income are also accompanied by increases in FFCO₂ emissions associated with an increase in energy demand (Cole and Neumayer 2004; Hubacek et al. 2007; Feng et al. 2009; Poumanyvong and Kaneko 2010).

Physical properties of an urban area such as urban form and location can also have an effect on the amount of FFCO₂ emissions. For instance, dense/compact neighborhoods or mixed land-use that encourage walking, biking, and utilization of public transportation tend to reduce FFCO₂ emissions (Newman and Kenworthy 1989; Jenks et al. 1996; Norman et al. 2006; Gomez-Ibanez et al. 2009). In contrast, suburbanization/urban sprawl with low density development induces more travel and thus contributes to an increase in FFCO₂ emissions, especially those associated with automobile use (Newman and Kenworthy 1989; Gomez-Ibanez et al. 2009; Dodman 2011). For example, Norman et al. (2006) found that transportation requirements for low density development account for per capita FFCO₂ emissions four times that of high density development. Furthermore, the location of an urban area also has a direct impact on energy use and FFCO₂ emissions. This is most pronounced in the building sector where space heating and cooling account for the largest share (37 %) of energy use (DOE 2012).

Building characteristics such as size, type, age, building orientation, building envelope, and appliance use also influence the amount of energy consumed and FFCO₂ emitted. Not surprisingly, larger buildings typically require more energy for space cooling and heating (Heiple and Sailor 2008). Building type, such as single-family homes versus apartment units, require different amounts of energy consumption. For example, several studies such as Hojjati and Wade (2012) and Ewing and Rong (2008) have shown that single-family detached houses use more energy than multi-family houses of the same total floor area. This is primarily due to

the larger surface area-to-volume ratio associated with single-family housing, which increases heating/cooling loss (Smeds and Wall 2007).

To quantify the influence of these drivers of FFCO₂ emissions in Salt Lake County, we employed the STIRPAT (Stochastic Impact by Regression on Population, Affluence, and Technology) regression model. The STIRPAT modeling approach was developed by York et al. (2003), as a reformulation of the IPAT model, first developed by Ehrlich and Holdren (1971). The IPAT model is a simple relationship used to express environmental impact (I) in terms of three driver variables: population (P), affluence (A), and technology (T) (York et al. 2003). STIRPAT has been employed to analyze the drivers of environmental impact such as the CO₂ emissions and climate change (Dietz and Rosa 1997; Fan et al. 2006; Lankao et al. 2009). York et al. (2003) reformulated the IPAT model into a non-linear form:

$$I = aP^bA^cT^d\varepsilon \quad (1)$$

where, I is the environmental impact; P is the population; A is affluence; T is technology; a , b , c , d are the parameters to be estimated; and ε is the error term.

A linearized form of the STIRPAT model can be expressed as:

$$\log I = a + b(\log P) + c(\log A) + d(\log T) + \varepsilon \quad (2)$$

In our application of this model to Salt Lake County, the spatial unit of analysis is the US census block group. There are a total of 612 census block groups in Salt Lake County. We define the environmental impact (I) as the FFCO₂ emissions from the residential sector. Three different population-related variables are used in this study to represent the IPAT population variable: total population, housing units per capita, and housing units per land area. All of these population-related variables were obtained from the 2010 US Census. Furthermore, the number of housing units per land area provides an indication of compact development, a policy-relevant metric important to land-use planning in many US locations. The per capita income is used to represent the affluence variable (A). The income data is obtained from the US Census Bureau's 2013 American Community Survey (ACS). Lastly, building age is used to represent the IPAT technology variable (T). The building age and total floor area information were obtained from the Salt Lake County's Assessor's Office. To account for variation in building size within the building age variable, an area-weighted mean building age is calculated for each block group.

The final form of our STIRPAT formulation in Salt Lake County can be expressed as:

$$\begin{aligned} \ln(\text{FFCO}_2) = & \alpha + \beta_1 \ln(\text{population}) + \beta_2 \ln(\text{housing units per capita}) \\ & + \beta_3 \ln(\text{housing units per area}) + \beta_4 \ln(\text{building age}) \\ & + \beta_5 \ln(\text{income per capita}) + \varepsilon \end{aligned} \quad (3)$$

where, \ln is the natural logarithm; α is the intercept; β_1 , β_2 , β_3 , β_4 , β_5 are the parameters to be estimated; and ε is the error term. Standard Ordinary Least Squares is employed to solve equation 3.

Five variations of the above regression model were constructed reflecting different discrete subsets of the data:

- Model 1: all Salt Lake County
- Model 2: High income block groups

- Model 3: Low income block groups
- Model 4: Within Salt Lake City boundary
- Model 5: Outside Salt Lake City boundary (the rest of the County)

Fig. S1 shows the five subsets of the block groups (see Supplementary Material). We identified two block groups as outliers based on the regression residuals. Thus, these two block groups were excluded from the final regression analysis. These block groups contain the Salt Lake City International Airport in the northwest of the county and the State Prison in the south of the county (Fig. S1b).

Results

Descriptive statistics

Table 2 presents the FFCO₂ emissions by economic sector and sub-sector in Salt Lake County and Salt Lake City in addition to a ratio of the city to county emissions. The 2011 FFCO₂ emissions for Salt Lake County are 3.17 MtC. The FFCO₂ emissions in the mobile sector represent the largest single emitting sector in the county (1.61 MtC) followed by the residential sector (0.66 MtC). Within Salt Lake City, the total FFCO₂ emissions are 0.85 MtC accounting for approximately 27 % of the County's total. As with the county emissions, the mobile sector is the largest emitter (0.44 MtC) followed by the residential sector (0.14 MtC). Within the mobile sector, the contribution of the Salt Lake City International airport emissions to the total county airport emissions is large (85 %) owing to the fact that the airport is within the city (Fig. S1b).

The population ratio of Salt Lake City to the County, 0.18, can be compared to the emissions ratio in sectors expected to follow population, thereby providing some initial insight into the relative emission intensities in the city versus the county.

The proportion of residential emissions in Salt Lake City (21 %) is somewhat larger than the population proportion (18 %) though probably within the range of uncertainty in the

Table 2 Fossil fuel CO₂ emissions for the year 2011 in Salt Lake County and Salt Lake City by economic sector and sub-sector. Values in the parentheses indicate the percentage of the county total FFCO₂ emissions. Units: million metric tonnes of carbon (MtC)

Sector/Sub-sector	Salt Lake County Total FFCO ₂ emissions (MtC)	Salt Lake City Total FFCO ₂ emissions (MtC)	City/County ratio
Commercial	0.24 (7.7 %)	0.11 (13.3 %)	0.46
Residential	0.66 (20.8 %)	0.14 (16.2 %)	0.21
Industrial	0.40 (12.6 %)	0.08 (9.1 %)	0.19
ElecProd	0.26 (8.2 %)	0.08 (9.9 %)	0.32
Mobile	1.61 (50.7 %)	0.44 (51.5 %)	0.27
Non-road	0.13 (4.1 %)	0.02 (2.4 %)	0.16
Airport	0.11 (3.3 %)	0.09 (10.7 %)	0.85
Onroad	1.36 (42.9 %)	0.32 (37.6 %)	0.23
Railroad	0.01 (0.4 %)	0.01 (0.9 %)	0.56
Total	3.17	0.85	0.27

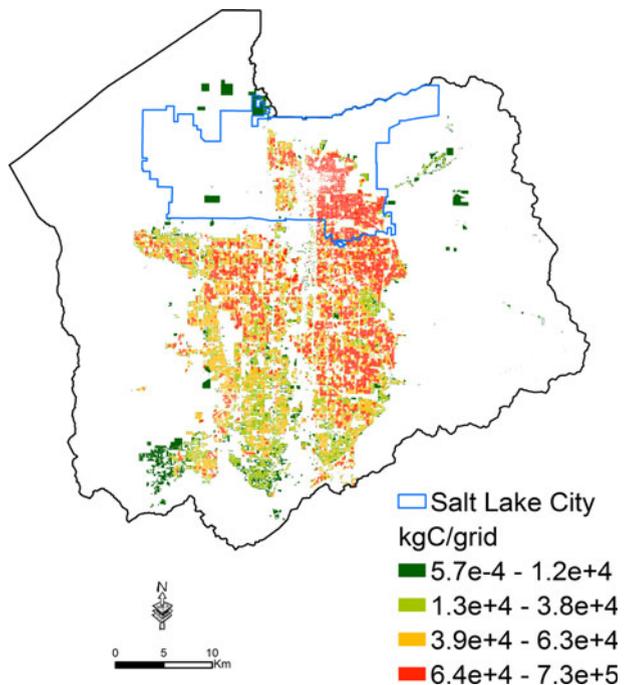
estimation. This suggests that city dwellers have a slightly higher per capita residential FFCO₂ emissions than those living in the remainder of the county. Similarly, a slightly higher proportion of onroad emissions are generated within the city (23 %) relative to the city population. However, because onroad emissions are not a direct function of in situ population, the greater onroad emissions proportion could be the result of many factors such as the greater flow of traffic to the city's commercial centers. Finally, the city commercial sector emissions are considerably over-represented in relation to the population proportion, accounting for 46 % of total county FFCO₂ emissions. This implies that a large proportion of the commercial activity occurs within the city – consistent with city's role as a commercial center within the county.

In the analysis that follows, we focus on the residential and the onroad sectors as these sectors are the largest FFCO₂ contributors in the Salt Lake domain and represent sectors that may be most amenable to policymaking at the local level.

The residential sector

Figure 1 shows the FFCO₂ emissions from the residential sector in gridded form (0.002 × 0.002° spatial grid or ~190 m × 190 m). The largest residential FFCO₂ emissions (>64 tC per grid cell) are located primarily on the eastern side of the county (using the Interstate 15 as a north–south dividing line). This high-emitting area consists of predominantly detached single-family housing units and large apartment complexes with more than 5 units. The detached single-family housing units on the east side are also associated with slightly larger average building floor area (2600 ft² on the eastern side versus 2450 ft² on the western side), leading to more heating and cooling demand, all else being equal.

Fig. 1 2011 residential sector FFCO₂ emissions represented in 0.002 × 0.002° grid cells. Legend color categories represent quartile boundaries



In order to examine the drivers of residential emissions, we have aggregated the building-level FFCO₂ emissions to census block groups, where data on demographics and economics are consistently available. Figure 2a–d show the spatial distribution of the FFCO₂ emissions for each block group and normalized by unit area, population and housing units, respectively. The largest total residential FFCO₂ emissions are found in the large census blocks to the east, west and south of the city center. When normalized by area, large emissions are concentrated in the smaller block groups on the eastern side of the county. When normalized by population, the largest per capita residential emissions are located predominantly in the eastern half of the county. When normalized by number of housing units, the largest emitting census block groups reveal a more complicated pattern with high values located in the more suburban areas

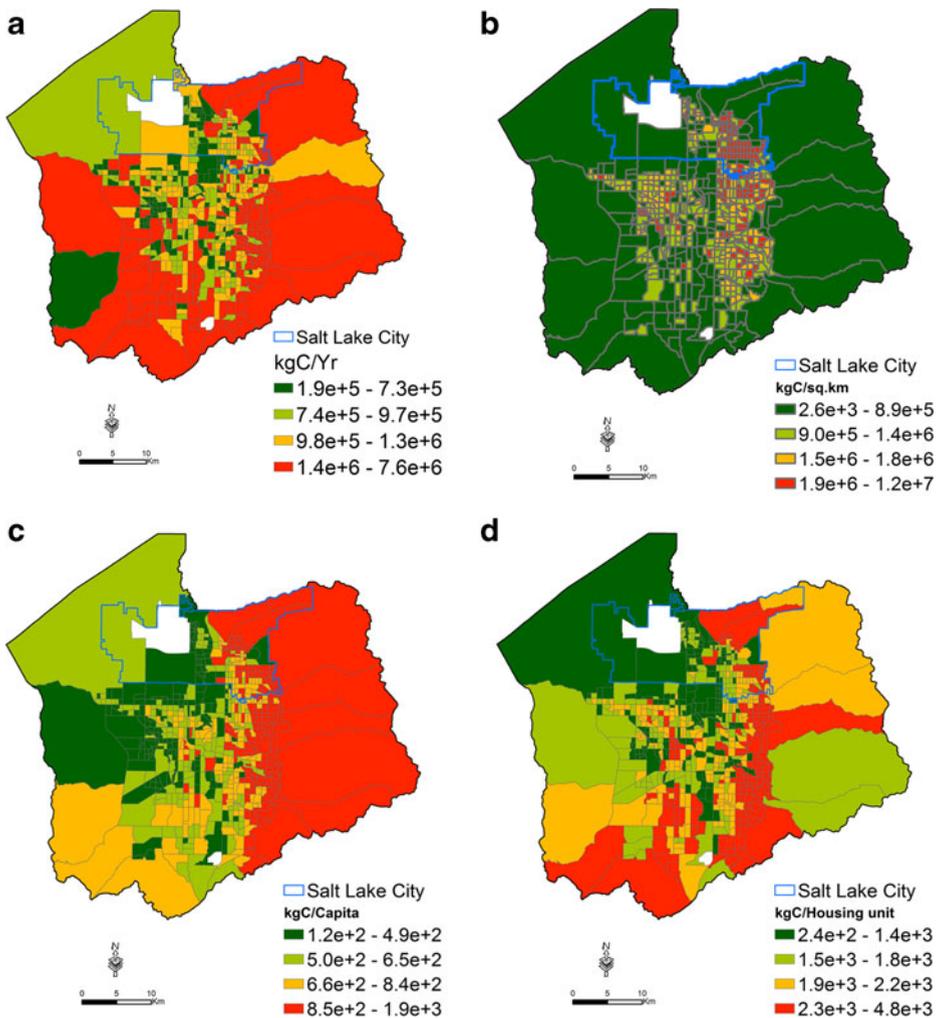


Fig. 2 2011 residential sector FFCO₂ emissions aggregated to the census block group spatial scale. **a** total emissions; **b** emissions per unit area; **c** emissions per capita; **d** emissions per housing unit. Legend color categories represent quartile boundaries

as opposed to either the rural or urban block groups. These simple normalizations will be explored more thoroughly in the regression analysis below.

The onroad sector

Figure 3 presents the onroad FFCO₂ emissions in gridded form. In general, grid cells that have large onroad FFCO₂ emissions contain greater amounts of primary and secondary road types with the city typically containing a higher density of these road types per grid cell (Fig. 3a). Moreover, primary and secondary roads often contain a greater number of lanes (4 or more) and carry more traffic than local roads.

Primary roads emit 0.67 MtC, accounting for the largest share (49 %) of onroad FFCO₂ emissions in Salt Lake County. Secondary roads emit 0.39 MtC (29 %) and local roads emit 0.30 MtC (22 %). Figure 4a shows the emissions density (FFCO₂ emissions per road length – kgC/km) for all road types in the Salt Lake County domain emphasizing the top 5, 10, and 20 %. The north–south Interstate 15 contains the largest continuous onroad emissions density followed by smaller segments of roadway in various locations throughout the county. Many of these high density segments are outside of Salt Lake City and associated with two dominant categories of primary roads: interstates (e.g. Interstates 215 and 80) and principal arterials (e.g. state route 154).

Figure 4b shows the distribution of onroad FFCO₂ emissions density in the primary and secondary road categories. The primary roads exhibit a narrower distribution of values than the secondary roads and a larger median emissions density value. This suggests that the primary roads have less variation in traffic volume, fleet distribution, and/or driving conditions than secondary roads. The primary roads also exhibit four other smaller peaks, which are associated with the different sub-classes of primary roads which contain differing number of lanes (e.g. 2, 4, 10, 12 lane interstates – see Fig. S3).

Since primary roads typically contain a larger number of lanes and traffic volume, it is useful to control for these factors and examine the onroad emissions normalized by the VMT

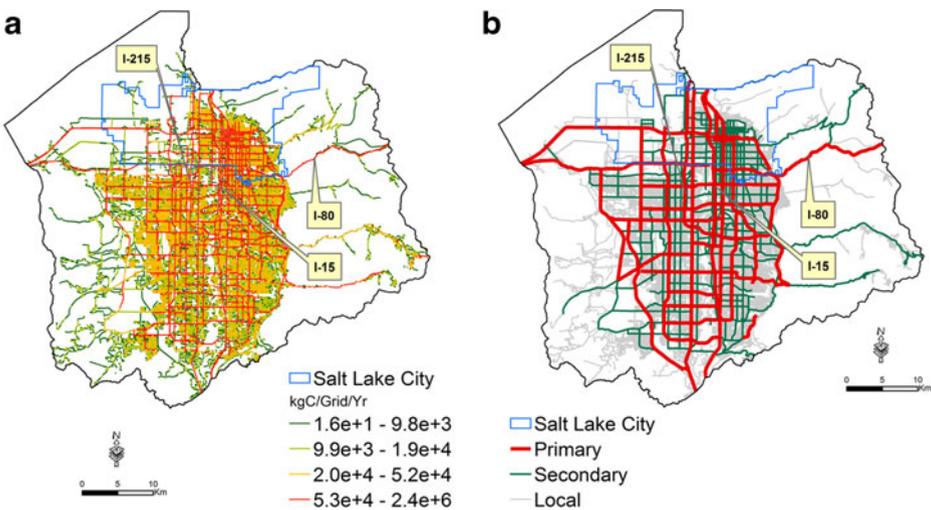


Fig. 3 Salt Lake County onroad network. **a** 2011 onroad FFCO₂ emissions represented in 0.002 × 0.002° grid cells. Legend color categories represent quartile boundaries; **b** road types

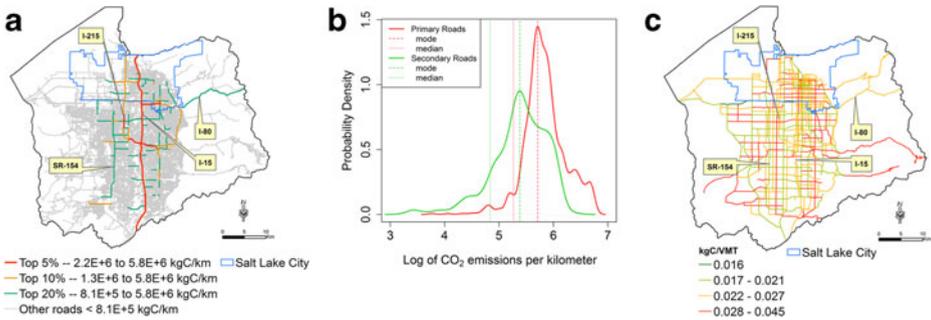


Fig. 4 2011 onroad FFCO₂ emissions. **a** emissions density (emissions per road length – kgC/km) on all road types; **b** probability density distribution of onroad FFCO₂ emissions density for primary and secondary road types; **c** emissions intensity (emissions per vehicle mile traveled – kgC/VMT) on primary and secondary roads

value (we refer to this as “emissions intensity” with units kgC/VMT – Fig. 4c). Such a normalization reveals roads for which either the fleet composition (proportion of commercial trucks versus passenger cars), the mean travel speed or the driving conditions, deviate from the mean. Average travel speed and driving conditions influence the efficiency of vehicle travel and hence the quantity of FFCO₂ emitted per mile traveled. In the Salt Lake County domain, road segments that exhibit large FFCO₂ emissions density, such as Interstate 15, do not exhibit large emissions intensity. In contrast, several road segments that do not exhibit large emissions density have larger emissions intensity. Most of these roads are secondary roads (state or county routes) with 2–4 lanes and traffic lights.

Through the use of traffic monitoring, we are able to examine the temporal structure of Salt Lake County onroad FFCO₂ emissions. Figure 5a shows the annual average hourly county-integrated weekday onroad FFCO₂ emissions. The emissions exhibit maxima during the morning and evening rush hours with the evening maxima (4–6 pm) larger and with a wider distribution than the morning (7–8 am). FFCO₂ emissions reach a minimum during the nighttime hours of 11 pm to 3 am. However, weekend onroad FFCO₂ emissions only show maxima during the evening hours (3–5 pm) (Fig. 5b).

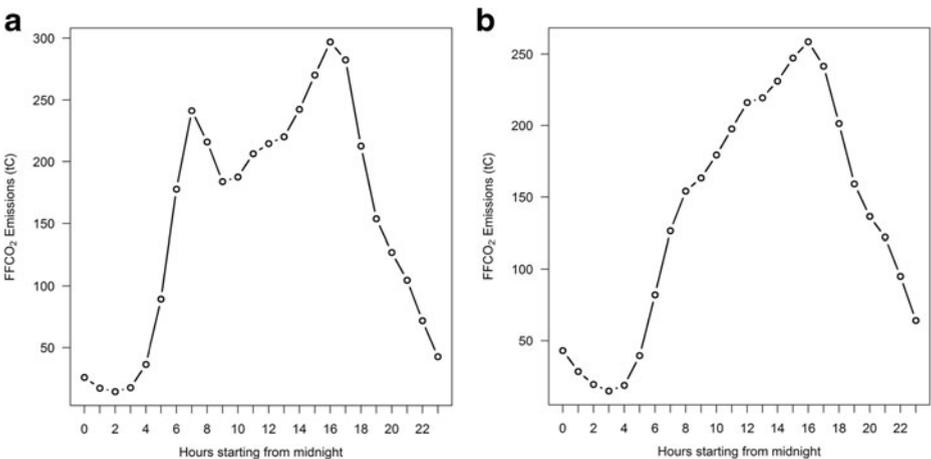


Fig. 5 Annual average hourly (US Mountain Standard Time Zone) onroad FFCO₂ emissions for the vehicles on all roads in Salt Lake County. **a** weekdays; **b** weekends

Figure 6 shows the same information but in a spatially explicit form (for the Salt Lake City sub-domain). In general, larger FFCO₂ are emitted on the primary and secondary roads at any given hour of a day. Emissions between 3 pm – 7 pm are the largest followed by between 9 am – 3 pm. These large emissions are found in the downtown and the eastern side of the city. FFCO₂ emissions diminish after 9 pm.

Analysis

Residential FFCO₂ drivers

The STIRPAT regression results applied to the residential FFCO₂ emissions are presented in Table 3 (for descriptive statistics, correlation matrix, and spatial distribution maps, see supplementary information, Tables S1-S6, Fig. S2). The adjusted R² values range from 0.64 to 0.78. Model 4 (census block groups within Salt Lake City) has the highest adjusted R² value of 0.78 while Model 3 (census block groups with lower mean income) has the lowest (0.64).

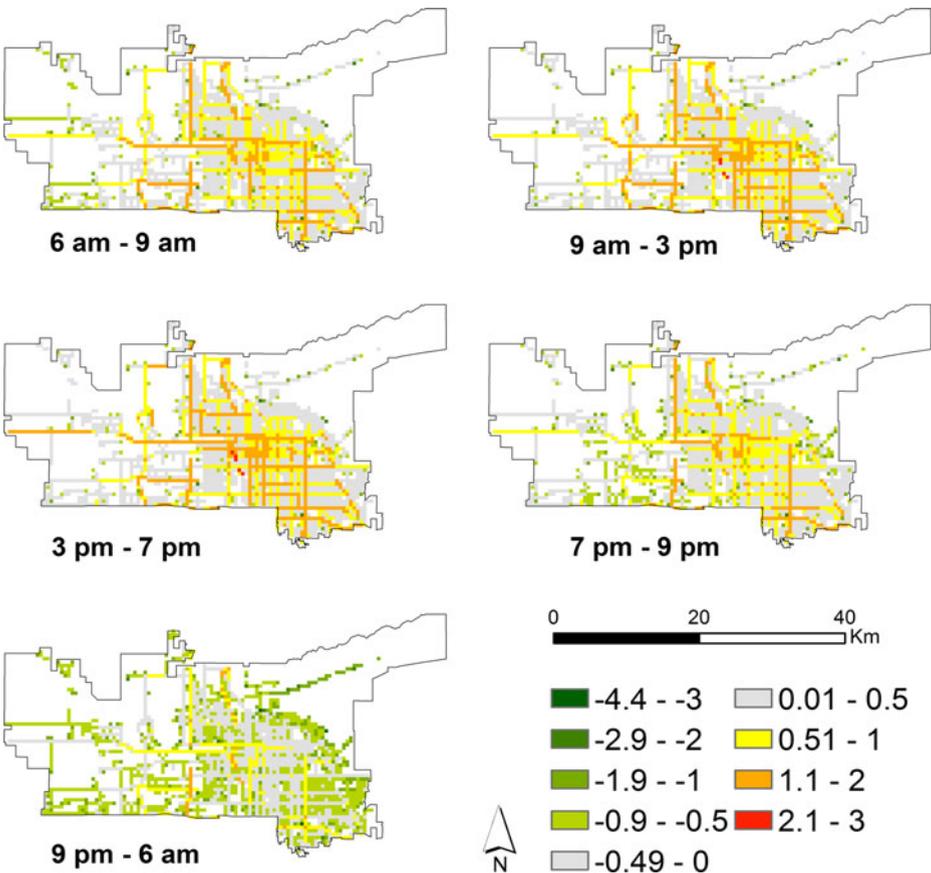


Fig. 6 Salt Lake City annual average hourly onroad FFCO₂ emissions represented in 0.002 × 0.002° grid cells. Emissions are represented as the deviation from the 24-h logged median value in five time bins

Table 3 Regression model coefficients and statistics

Variables	Model 1: County		Model 2: High Income		Model 3: Low Income		Model 4: City		Model 5: Outside City	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Intercept	0.46	0.42	1.19	0.99	4.43***	1.03	1.37*	0.67	-0.47	0.53
Population (log _e)	0.94***	0.03	0.95***	0.05	0.85***	0.05	0.93***	0.06	0.97***	0.03
Housing units per capita (log _e)	0.21***	0.04	0.11	0.08	0.40***	0.08	0.37***	0.07	0.13*	0.06
Housing units per area (log _e)	-0.05***	0.01	-0.03	0.02	-0.04*	0.02	-0.01	0.02	-0.06***	0.01
Building age (log _e)	0.17***	0.03	0.14***	0.05	0.14**	0.05	0.06	0.05	0.25***	0.03
Income per capita (log _e)	0.63***	0.02	0.54***	0.07	0.31***	0.09	0.57***	0.03	0.67***	0.03
Adjusted R ²	0.77		0.74		0.64		0.78		0.77	
Degrees of freedom	604		146		147		135		463	

Coeff coefficient, *SE* standard error

*** $p < 0.001$

** $p < 0.01$

* $p < 0.05$

Across all of the models, the population variable is significant at the 0.01 % level and exhibits a weak sub-linear relationship suggesting that FFCO₂ emissions increase in very nearly direct proportion with population across census block groups, all else being equal. Population has the greatest proportional influence on the FFCO₂ emissions among the independent variables considered. When using only census block groups with a mean income in the lowest income cohort, the relationship is more sub-linear, suggesting that a 1 % increase in population across low income census block groups is met with a 0.85 % increase in FFCO₂ emissions.

Per capita income is the next most influential independent variable with coefficient values of approximately +0.6, except when subsetting by low-income where the coefficient is reduced to +0.3. This suggests that as income rises, FFCO₂ emissions increase as well, though at a sub-linear rate, all else being equal. For census block groups with a lower mean per capita income, the influence of income is roughly half that of the general population. This suggests that increments of wealth among census block groups with higher mean per capita income lead to greater proportional increases in FFCO₂ when compared to census block groups with lower mean income.

Housing units per capita exhibits a relationship to residential FFCO₂ emissions across census block groups, though the importance varies quite a bit among the models. Household size (i.e., number of people living in a housing unit), a more intuitive metric, is the reciprocal of housing units per capita. For the county as a whole, there is a positive relationship between housing units per capita and FFCO₂ emissions such that a 1 % decline in household size is associated with 0.21 % rise in FFCO₂ emissions, all else being equal. This suggests that block groups with a greater average number of individuals per household (but the same total block group population) have lower FFCO₂ emissions though the decline is not directly proportional to household size, but sub-linear. The influence of household size is much more pronounced for city and low income residents than for the population as a whole with slope coefficients of +0.37 and +0.40 for city and low income residents, respectively. This result suggests that if one were to compare two census block groups for which total population, total housing units, building age, and mean per capita income were identical, the census block group with a greater average household size

(more individuals per housing unit) would have lower FFCO₂ emissions though not in direct proportion to the difference in household size. The fact that this effect is more pronounced for city block groups and those with a lower mean income may suggest that the efficiencies of household size are exploited to a greater degree in these subsets of the whole county domain.

A related variable, housing units per area, has little impact on FFCO₂ emissions. Furthermore, the coefficient for models 2 and 4 are not significant at the 0.05 level. Hence, for two census block groups in which per capita income, household size, building age, and population were identical, the census block group with the greater number of housing units would have smaller FFCO₂ emissions, though the effect is barely discernible from zero. This suggests that, to the extent compact development has occurred within Salt Lake County, it has had little impact on FFCO₂ emissions.

Building age shows a positive relationship with residential FFCO₂ across all of the models as expected from the prior constraint on the NE-EUI with age. In general, older residential buildings are less energy-efficient due to older HVAC (heating, ventilation and air-conditioning) systems, less insulation, single-pane windows and leakier building envelopes. With the same demand and fuel composition, this will lead to greater FFCO₂ emissions (Huang et al. 1991; Ewing and Rong 2008; DOE 2012). The dependence of FFCO₂ emissions on building age show greater sensitivity when examining only census block groups outside the city (slope coefficient of 0.25) versus those within (slope coefficient of 0.06). This is likely due to the differing mix of building types within the city versus the county and the fact that each building type has a different ratio of old versus new NE-EUI values.

Onroad FFCO₂ patterns

The road segments accounting for the top 20 % of the FFCO₂ onroad emissions density, shown in Fig. 4a, can be explored in more detail in order to isolate spatio-temporal patterns and potential policy options for FFCO₂ emissions mitigation (Fig. 7). These road segments have

Fig. 7 Top 20 % of onroad FFCO₂ emissions density and existing public transit routes

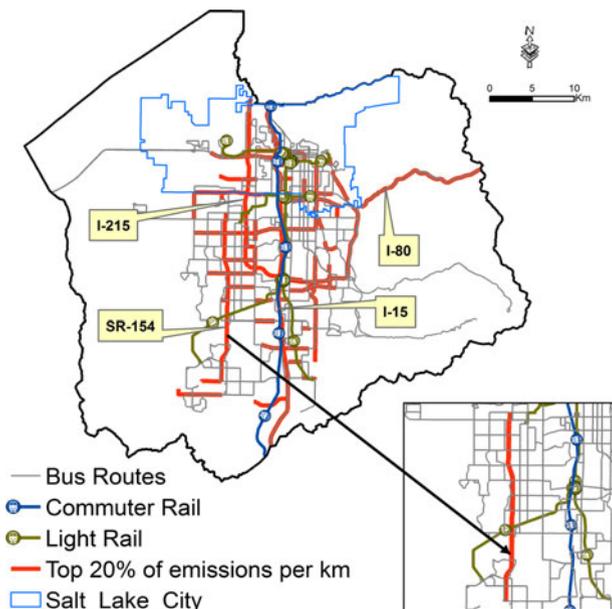


Table 4 Statistical description of the road segments accounting for the top 20 % of FFCO₂ onroad emissions density

Road Type	Total Road Length (km) % total in parentheses	Total Emissions (tC)	Emissions density (tC/Km)		
			Min	Median	Max
Primary	241 (66 %)	470,250 (77 %)	813	1453	5766
Interstates	154 (42 %)	384,037 (63 %)	1033	2336	5766
Other primary roads	87 (24 %)	86,213 (14 %)	813	960	1621
Secondary	127 (34 %)	137,812 (23 %)	806	1054	2802
Total	368 (100 %)	608,062 (100 %)			

emissions density values ranging from ~800 tC/km to ~5800 tC/km with interstates accounting for the largest share (63 %), followed by secondary roads (23 %) and other primary roads (14 %) (Table 4).

We compare these dominant road segments with the existing public transit networks in order to highlight potential policy opportunities aimed at lowering onroad FFCO₂ emissions. Salt Lake County public transit includes bus, commuter rail, and light rail systems (Fig. 7). Bus routes are present throughout the county and provide service primarily on secondary roads. The bus routes are generally aligned with the road segments that have high emissions except on State Route 154 (Fig. 7, insert map). The commuter and light rail networks, however, are less extensive and hence, could offer some policy options for onroad FFCO₂ mitigation. Currently, both commuter and light rail (TRAX) systems provide services mainly along the central north–south corridor with less service along the east–west corridor. Hence, these east–west corridors that align with large onroad FFCO₂ emissions may be candidates for optimal light rail expansion. Road corridors such as Interstate 215 and 80, and state route 154 are possible targets. Were light rail expansion along these lines able to displace 25 % of the existing traffic volume, this would mitigate ~50,000 tC/year, accounting for 8 % of the top 20 % presented in Fig. 7 and Table 3. Using the current social cost of carbon (SCC) of \$40/tonne of CO₂ (EPA 2015), this equates to ~7 million dollars in carbon offset value.

Discussion

Salt Lake City has plans in place that include greenhouse gas reduction targets. For example, the “Salt Lake City Green: Energy and Transportation Sustainability Plan 2011” aims to reduce greenhouse emissions to 17 % below 2005 levels by 2020 (Salt Lake City 2011). Likewise, the “Salt Lake City Sustainable Plan 2015” sets environmental sustainability goals through air quality improvement, energy use reduction, and zero-carbon transportation services. For example, the city aims to reduce total energy use in buildings by 5 % by the end of 2015 through household solar energy and incentives to meet LEED building efficiency standards. For the transportation sector, the city aims to reduce VMT by 6.5 %, increase clean and alternative fuel vehicles to 15 % of the city fleet, extend the TRAX line, increase bike lanes by 50 %, and increase the efficiency of traffic flow via improved traffic-signal timing (Salt Lake City 2015). The FFCO₂ analysis presented here may offer some specific guidance on the operationalization of these goals.

The residential sector

Quantification and analysis of residential buildings in Salt Lake County at fine space and time scales offer greater insight into the drivers of emissions than can be gleaned from zero-dimensional (i.e. simple pie-chart) representations of FFCO₂ emissions. The spatial pattern of residential emissions, normalized by population or number of housing units (Figs. 1 and 2), suggests that mitigation might find efficiencies in application by knowing where FFCO₂ emissions are largest and why. Simple normalization of the spatial FFCO₂ emissions indicate that policies targeted to building envelopes versus occupant behavior would likely emphasize different geographies. For example, policy targeting behavioral change may find the greatest gain in the eastern half of the county while policy targeting building envelopes may be most effective targeting suburban pockets in the east and south portions of the county.

For a deeper and potentially more nuanced guide to climate mitigation policy options, the STIRPAT regression results are informative. Of the variables considered here, FFCO₂ emissions are most sensitive to population and per capita income. The proportional relationship to population begs comparison to recent work exploring scaling relationships between city size and a number of urban attributes (Bettencourt et al. 2007; Cottineau et al. 2015). Indeed recent work examining FFCO₂ emissions across cities of varying size remains unclear regarding whether or not FFCO₂ emissions scale sub-linearly or super-linearly with population (Fragkias et al. 2013; Oliveira et al. 2014; Arcaute et al. 2015). The results presented here, albeit at the sub-city scale, suggest linear or very slightly sub-linear scaling. Perhaps most interesting is the shift in the linear relationship when the lowest income group is examined in isolation. In the low-income block groups, FFCO₂ emissions do not rise proportionally with population but at a lessened rate (Table 3).

This is similar to the dynamics found in relation to per capita income, the other high-influence variable in the regression analysis. Wealthier census block groups show FFCO₂ emissions with nearly twice (+0.54 versus +0.31) the sensitivity to per capita income than the lower income census block groups. This suggests a non-linear relationship between FFCO₂ emissions and per capita income. Increasing increments of income in the higher income block groups are met with greater increases in FFCO₂ emissions compared to the lower income block groups, all else being equal. Though our data cannot precisely identify the dynamics at work, we can speculate. Energy use behavior, lifestyle, and income expenditure preferences could explain the emission differences between the high- and low-income block groups (Haas et al. 1998; Bin and Dowlatabadi 2005; Hubacek et al. 2007). For example, it is possible that in the lower income block groups, households will allocate increases in income to other priority commodities such as food or clothing first, before allocation to greater energy demand for space heating/cooling or water heating. Or additional increments in wealth among the lower income block groups correlate with improved housing with accompanying higher efficiency space heating/cooling systems. Hence, increased heating/cooling comfort is delivered with little change in energy requirements. Conversely, added increments of wealth among the higher income block groups may correlate with larger homes with little heating/cooling equipment efficiency improvement as that home attribute is already saturated. Furthermore, there is evidence that high-income residents set thermostats during winter at a more desirable comfort level given the greater amount of disposable income that can be devoted to energy costs in comparison to low-income residents (Hunt and Gidman 1982; Santamouris et al. 2007; Walker and Meier 2008).

From a policy perspective these results suggest that emissions reductions may find greatest efficacy among the high income census block groups. Furthermore, policies aimed at energy cost savings via improved building envelope efficiency may not be the most effective modality. Rather, appeals to personal responsibility or enabling better feedback information loops may offer advantages. An example of this is programs in some utility ratepayer service areas that offer performance comparisons of individual ratepayers with surrounding averages that are included in utility billing statements (Opower 2015; Asensio and Delmas 2015). Centralized online presentation of spatial maps like those described here, advertised by utilities or city and county government, may also be effective.

Our findings of a negative relationship between household size and FFCO₂ emissions are consistent with other studies where larger households likely benefit from economies of scale associated with space and energy use (e.g. Cole and Neumayer (2004), Druckman and Jackson (2008), Lin et al. (2013), Pachauri (2004)). Furthermore, as with per capita income, the influence is sensitive to wealth and geography. For example, FFCO₂ emissions among low income block groups show nearly four times the sensitivity to household size than the high-income block groups. City versus non-city block groups show three times the sensitivity. This suggests that low income block group inhabitants avail of the efficiency gains of co-habitation to a much greater degree than inhabitants of high-income block groups. This could be thought of as high-income individuals having space/water heating energy use that is tied to individual needs, regardless of the physical efficiency of co-habitation, whereas low-income individuals have space/water heating energy-use that is more tied to building infrastructure, allowing energy use per person to decline as more individuals occupy a given structure.

Somewhat surprisingly, our results do not seem to support other research that finds lower emissions associated with compact development (Holden and Norland 2005; Norman et al. 2006; Ewing and Rong 2008). Though the regression coefficient is negative (less FFCO₂ emitted for greater housing density), the magnitude is consistently less than 0.1 across the models. However, most of the density effect owes to onroad transportation reductions garnered with greater housing density as opposed to building space/water heating, the primary source of residential building FFCO₂ emissions in our production-based framework (Ewing et al. 2003; Glaeser and Kahn 2010).

The onroad sector

FFCO₂ emissions density (emissions per road length) is a useful metric to identify the spatial distribution of FFCO₂ emissions for a road type across the landscape (Kinnee et al. 2004). Emissions intensity (emissions per vehicle mile travel), by contrast, provides insights on the driving behavior, traffic conditions and fleet composition—elements affecting the fuel economy (miles per gallon, mpg) and fuel efficiency of a vehicle (Mendoza et al. 2013). Analysis of the spatial distribution using emissions density and intensity metrics can be useful for policy makers to find the cost-effective solutions to alleviate onroad FFCO₂ as this sector contributes to nearly half of the Salt Lake County FFCO₂ emissions.

We find primary roads, especially some portions of the interstates, represent the largest 5 % of the emissions density (>0.22 MtC/km) in Salt Lake County (Fig. 4a). This is due to the nature of interstates which typically have greater traffic volumes and a greater number of lanes (usually 4 or more) compared to other road types. To assist with the 6.5 % reduction in VMT outlined in the Salt Lake City Sustainable Plan 2015, our results suggest that an effective strategy to mitigate FFCO₂ emissions may be to target these high-emitting road segments first.

These roads already account for ~28 % of the Salt Lake County's VMT and contribute to ~20 % (~0.27 MtC) of the County's total emissions.

When examining high-emitting road segments in relation to current public transportation systems in Salt Lake County, we find opportunities for alignment with public transportation expansion. These road segments account for nearly half of the county's onroad FFCO₂ emissions (Tables 2 and 4). Policies to reduce FFCO₂ could consider expanding existing public transportation such as light rail or bus rapid transit (BRT) service to some of these road segments. All modes of public transportation including light rail, BRT and buses emit less FFCO₂ per passenger mile than private passenger cars (Vincent and Jerram 2006). For instance, O'Toole (2008) estimated the amount US average emissions per passenger mile as 0.54 and 0.36 lb of FFCO₂, respectively for passenger cars and light rail. Lochner (2013) estimated expansion of the light rail system (e.g. TRAX blue line) in the county would increase ridership by at least 12,000–14,000 passengers per day. Lochner also estimated that if the current light rail service was "turned off" for a day, 29,000 vehicles per day would be added along the north–south corridors. Finally, a study by Ewing et al. (2014) showed that the extension of the TRAX red line serving the University of Utah campus reduced the number of annual average daily traffic by at least 7500. This saves ~362,000 gal of gasoline and prevents ~7 million pounds of FFCO₂ from being emitted annually.

In contrast to the pattern associated with FFCO₂ emissions density, road segments with high FFCO₂ emission intensity (>28 grams/VMT) are found on primarily secondary roads rather than primary roads (Fig. 4a). Secondary roads are designed for balancing between traffic mobility and land access with shorter distance and lower speed (up to 40 mph) by collecting the traffic from local roads and connecting them with primary roads. By contrast, primary roads are designed to offer a higher degree of traffic mobility at the greatest speed and for the longest uninterrupted distance (Federal Highway Administration 2015). Vehicles traveling at an average speed below 40 mph are less fuel efficient (hence, emit more FFCO₂) than when traveling at an average speed of 40–60 mph (Barth and Boriboonsomsin 2009).

Vehicles travelling on primary roads have a higher probability of maintaining a steady travel speed compared to secondary roads where traffic lights and traffic congestion are common (Barth and Boriboonsomsin 2009). Traffic lights and traffic congestion are obstacles that requires vehicles to make more frequent stops as well as increase vehicle idling time, frequent acceleration and deceleration (i.e., "stop-and-go" traffic) leading to poor fuel economy and increased FFCO₂ emissions per mile travelled. Hence, the functionality of the secondary roads suggests that lower traveling speed, traffic lights, and traffic congestions are drivers of the larger FFCO₂ emissions intensity. One of the strategies that will lower FFCO₂ emissions on these types of roads is to reduce vehicle idling time and stop-and-go traffic through improved traffic-signal timing (Frey et al. 2001; Madireddy et al. 2011). According to Koa Corporation (2011), improved traffic-signal timing in the Salt Lake City metropolitan area reduces average travel time by as much as 8 %, increases average speed by 8 %, decreases the number of stops by 17 %, and decreases fuel consumption by 5.9 %. Our results suggest that improving the traffic-signal timing where two high emission intensity road segments meet would yield the greatest benefits to FFCO₂ reduction on these secondary roads. Intersections where high emission intensity road segments meet account for ~46 % (or ~127,000 tC) of the FFCO₂ emissions of the high emission intensity cohort identified in Fig. 4c (FFCO₂/VMT > 0.028). Using the estimated fuel consumption reduction value reported by Koa

Corporation of 5.9 %, this would potentially reduce the amount of FFCO₂ by ~7500 tC. Using an SCC value of \$40/tonnes of CO₂ (EPA 2015), this equates to \$1,097,334 in carbon offset value.

Conclusions

We have applied the Hestia FFCO₂ emissions quantification approach to Salt Lake County in order to demonstrate potential for greenhouse gas emissions mitigation policy guidance. Some departures from the previously described Hestia methodology were required due to advances in data availability and idiosyncrasies associated with the Salt Lake spatial domain.

The initial breakdown of FFCO₂ emissions shows the onroad FFCO₂ emissions as the dominant sector (42.9 %) followed by the residential (20.8 %) and industrial (12.6 %) sectors. The residential and onroad emissions in the city are somewhat overrepresented relative to population proportions. This is particularly true for the commercial sector due to the importance of the city as the commercial hub of the county.

Simple normalization of the residential emissions shows distinct spatial patterns with per capita emissions higher in the eastern half of the county but normalization per housing unit exhibiting a much more dispersed pattern consistent with suburban growth. We applied the STIRPAT regression analysis to better understand the driving factors of the residential building FFCO₂ emissions. At a scale of the census block group, population, per capita income, household size, and building age were found to have a statistically significant influence on FFCO₂ emissions. However, housing density had little to no effect on FFCO₂ emissions. We find that the level of influence of per capita income and household size on FFCO₂ emissions are themselves sensitive to per capita income. Increases in per capita income among high income block groups shows almost twice the impact on FFCO₂ emissions than the low income block groups (+0.54 % versus +0.31 % rise in FFCO₂ per 1 % rise in per capita income, all else being equal). Increases in household size among low income block groups results in nearly four times the impact on FFCO₂ emissions compared to high income block groups (−0.40 % versus −0.11 % decline in FFCO₂ per 1 % rise in household size, all else being equal).

These results suggest that policies aimed at the residential sector may find greatest success if structured to target high-income groups through appeals to personal responsibility or via better information feedbacks (e.g. the “dashboard effect”, neighborhood comparisons). Both the per capita income and household size results suggest that the sensitivities relate less to infrastructure and more to choice and lifestyle. Awareness of energy or emitting intensity may be low among these groups or it may be triggered through simple outreach programs accessed to ratepayers through utility billing platforms.

Onroad emissions are dominated by the primary road category (49 %) followed by secondary (29 %) and local roads (22 %). Primary road FFCO₂ emissions exhibit a higher median emissions density value with less variance in comparison to secondary roads. This is likely a result of the driving characteristics on primary roads where vehicles operate at conditions closer to optimal efficiency relative to the stop-and-go style driving typical on secondary roads. As a result, secondary roads exhibit larger emissions intensity when compared to primary roads. We compare these high emitting road segments with existing public transportation networks and find opportunities for extension of for example, the existing light rail system. Doing so has the potential to offset approximately ~50,000 tC/year of FFCO₂

emissions, which equates to ~7 million dollars. Improving the traffic-signal timing where high emissions intensity roads intersect could improve the traffic flow and reduce the overall FFCO₂ emissions. Such improvements could potentially reduce the amount of FFCO₂ by ~7500 tC/year, equivalent to ~\$1 million in carbon offset value.

Our study has some caveats. The Hestia approach relies on a large and diverse suite of data and modeling constructs. Among these, there is little accompanying uncertainty. In many cases, uncertainty is challenging to assign based on the nature of the incoming data. Hence, a devoted effort is needed to generate uncertainty and propagate those uncertainties through the Hestia approach to provide an improved understanding of where results are more or less certain in space and time. This remains a high priority for future research.

There are a series of improvements that could be made to the underlying data sources themselves. For example, greater accuracy in the individual building level FFCO₂ emissions could be generated with individual address-level utility billing. This would allow for a better assignment of emissions to buildings with gas feeds versus those completely reliant upon electricity and improve the estimation with directly metered gas amounts. Though attempts have been made to acquire this data, there have been very few instances of success due to the concern over the privacy of ratepayer data. But, there is no question that directly metered data is a critical need in Salt Lake City and across the United States. A system similar to that used by health researchers when accessing individual health data is much needed and would provide a profound change in the quality of data and the questions science could answer regarding energy flows and carbon emissions.

Regarding the onroad FFCO₂ estimation, traffic data outside of the city of Salt Lake domain is currently very limited. Hence, onroad emissions are supported by varying levels of quality and further work could repair this disparity. Furthermore, data that provides a greater level of detail on vehicle type would improve emissions and allow for a better understanding of the drivers of onroad FFCO₂ emissions. Finally, the approach taken in the Hestia system is focused on a “production” style estimate of FFCO₂ emissions. Though a critical approach for partnership with atmospheric measurements of CO₂, this approach within the onroad sector leaves little understanding of the driving forces behind emissions. The alternative, transportation demand modeling, can solve this problem but relies on little empirical data. Combining the empirically-based approach used in Hestia with transportation demand modeling is a potentially powerful way to provide accurate space/time estimate of onroad emissions with a link to the socio-economic and engineering drivers. This combination would offer not only diagnostic but prognostic capability, sorely needed in efforts to mitigate onroad FFCO₂ emissions in urban areas.

Acknowledgements This research was supported by grants from the Department of Energy DE-SC-001-0624, the National Science Foundation grant EF-01241286, National Institute of Standards and Technology grant 70NANB14H321, and National Oceanic and Atmospheric Administration Climate Program Office’s Atmospheric Chemistry, Carbon Cycle, and Climate Program grant NA14OAR4310178. We also would like to thank Jerome Zenger, Kevin Bell, and Semih Yildiz for assisting with the data collection and inquiry.

References

- AirNav (2014) Airport information. <http://www.airnav.com/>. Accessed 9 Jan 2014
- Arcaute E, Hatna E, Ferguson P et al (2015) Constructing cities, deconstructing scaling laws. *J R Soc Interface* 12:20140745. doi:10.1098/rsif.2014.0745

- Asefi-Najafabady S, Rayner PJ, Gurney KR, et al (2014) A multiyear, global gridded fossil fuel CO₂ emission data product: Evaluation and analysis of results. *J Geophys Res Atmos* 119:2013JD021296. doi: 10.1002/2013JD021296
- Asensio OI, Delmas MA (2015) Nonprice incentives and energy conservation. *Proc Natl Acad Sci* 112:E510–E515. doi:10.1073/pnas.1401880112
- Barth M, Boriboonsomsin K (2009) Traffic congestion and greenhouse gases. *ACCESS Mag* 1:1–9
- Bettencourt LMA, Lobo J, Helbing D et al (2007) Growth, innovation, scaling, and the pace of life in cities. *Proc Natl Acad Sci* 104:7301–7306. doi:10.1073/pnas.0610172104
- Bin S, Dowlatabadi H (2005) Consumer lifestyle approach to US energy use and the related CO₂ emissions. *Energy Policy* 33:197–208. doi:10.1016/S0301-4215(03)00210-6
- Bréon FM, Broquet G, Puygrenier V et al (2015) An attempt at estimating Paris area CO₂ emissions from atmospheric concentration measurements. *Atmos Chem Phys* 15:1707–1724. doi:10.5194/acp-15-1707-2015
- US Census Bureau (2015) State & County QuickFacts. <http://www.census.gov/quickfacts/table/IPE120213/49035.00>. Accessed 7 Sep 2015
- Ciais P, Sabine C, Bala G et al (2013) Carbon and other biogeochemical cycles. In: Stocker TF, Qin D, Plattner G-K et al (eds) *Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, pp 465–570
- Cole MA, Neumayer E (2004) Examining the impact of demographic factors on air pollution. *Popul Environ* 26: 5–21. doi:10.1023/B:POEN.0000039950.85422.eb
- Collins M, Knutti R, Arblaster J et al (2013) Long-term climate change: projections, commitments and irreversibility. In: Stocker TF, Qin D, Plattner GK et al (eds) *Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, pp 1029–1136
- Cottineau C, Hatna E, Arcaute E, Batty M (2015) Paradoxical interpretations of urban scaling laws. *ArXiv E-Prints* 1507:7878
- Cox PM, Betts RA, Jones CD et al (2000) Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature* 408:184–187. doi:10.1038/35041539
- Dai A (2013) Increasing drought under global warming in observations and models. *Nat Clim Chang* 3:52–58. doi:10.1038/nclimate1633
- Dietz T, Rosa EA (1997) Effects of population and affluence on CO₂ emissions. *Proc Natl Acad Sci* 94:175–179
- Dodman D (2011) Forces driving urban greenhouse gas emissions. *Curr Opin Environ Sustain* 3:121–125. doi: 10.1016/j.cosust.2010.12.013
- DOE (2012) 2011 buildings energy data book. Office of Energy Efficiency and Renewable Energy, Department of Energy, Washington
- Druckman A, Jackson T (2008) Household energy consumption in the UK: a highly geographically and socio-economically disaggregated model. *Energy Policy* 36:3177–3192. doi:10.1016/j.enpol.2008.03.021
- Ehleringer JR, Schauer AJ, Lai C et al (2008) Long-term carbon dioxide monitoring in Salt Lake City. *AGU Fall Meet Abstr* 43:0466
- Ehleringer J, Pataki DE, Lai C, Schauer A (2009) Long-term results from an urban CO₂ monitoring network. *AGU Fall Meet Abstr* 33:0414
- Ehrlich PR, Holdren JP (1971) Impact of population growth
- EIA (2002) Distillate fuel oil sales for railroad use. US Energy Information Administration, Department of Energy. www.eia.gov/dnav/pet/pet_cons_821use_a_epd0_vrr_mgal_a.htm. Accessed 5 Jan 2002
- EIA (2013a) Fuel oil and kerosene sales. <http://www.eia.gov/petroleum/fueloilkerosene/>. Accessed 8 Jul 2013
- EIA (2013b) Refiner petroleum product prices by sales type. http://www.eia.gov/dnav/pet/pet_pri_refoth_a_EPJK_PTG_dpgal_a.htm. Accessed 8 Jul 2013
- EPA (2015) Social Cost of Carbon. <https://www3.epa.gov/climatechange/EPAactivities/economics/scc.html>. Accessed 30 Sep 2015
- EPA (2016) The 2011 National Emissions Inventory. <http://www.epa.gov/ttnchie1/net/2011inventory.html>. Accessed 3 Mar 2016
- Ewing R, Rong F (2008) The impact of urban form on U.S. residential energy use. *Hous Policy Debate* 19:1–30. doi:10.1080/10511482.2008.9521624
- Ewing R, Pendall R, Chen D (2003) Measuring sprawl and its transportation impacts. *Transp Res Rec J Transp Res Board* 1831:175–183. doi:10.3141/1831-20
- Ewing R, Tian G, Spain A, Goates J (2014) Effects of light-rail transit on traffic in a travel corridor. *J Public Transp*. doi:10.5038/2375-0901.17.4.6
- Fan Y, Liu L-C, Wu G, Wei Y-M (2006) Analyzing impact factors of CO₂ emissions using the STIRPAT model. *Environ Impact Assess Rev* 26:377–395. doi:10.1016/j.ear.2005.11.007
- Federal Highway Administration (2014) Field manual. <https://www.fhwa.dot.gov/policyinformation/hpms/fieldmanual/chapter1.cfm>. Accessed 11 Jul 2014

- Federal Highway Administration (2015) Flexibility in highway design chapter 3: functional classification. <http://www.fhwa.dot.gov/environment/publications/flexibility/ch03.cfm>. Accessed 20 Sep 2015
- Feng K, Hubacek K, Guan D (2009) Lifestyles, technology and CO₂ emissions in China: a regional comparative analysis. *Ecol Econ* 69:145–154. doi:10.1016/j.ecolecon.2009.08.007
- Fragkias M, Lobo J, Strumsky D, Seto KC (2013) Does size matter? Scaling of CO₂ emissions and U.S. urban areas. *PLoS ONE* 8:e64727. doi:10.1371/journal.pone.0064727
- Frey HC, Roupail NM, Unal A, Colyar JD (2001) Emissions reduction through better traffic management: an empirical evaluation based upon on-road measurements. CTE/NCDOT Joint Environmental Research Program, Raleigh
- Gately CK, Hutyra LR, Wing IS (2015) Cities, traffic, and CO₂: a multidecadal assessment of trends, drivers, and scaling relationships. *Proc Natl Acad Sci* 112:4999–5004. doi:10.1073/pnas.1421723112
- Glaeser EL, Kahn ME (2010) The greenness of cities: carbon dioxide emissions and urban development. *J Urban Econ* 67:404–418. doi:10.1016/j.jue.2009.11.006
- Gomez-Ibanez DJ, Boamert MG, Brake DR, et al (2009) Driving and the built environment: the effects of compact development on motorized travel, energy use, and CO₂ emissions. Oak Ridge National Laboratory (ORNL)
- Gurney KR, Law RM, Denning AS et al (2002) Towards robust regional estimates of CO₂ sources and sinks using atmospheric transport models. *Nature* 415:626–630. doi:10.1038/415626a
- Gurney K, Ansley W, Mendoza D et al (2007) Research needs for finely resolved fossil carbon emissions. *EOS Trans Am Geophys Union* 88:542–543. doi:10.1029/2007EO490008
- Gurney K, Mendoza D, Zhou Y et al (2009) High resolution fossil fuel combustion CO₂ emission fluxes for the United States. *Environ Sci Technol* 43:5535–5541
- Gurney KR, Razlivanov I, Song Y et al (2012) Quantification of fossil fuel CO₂ emissions on the building/street scale for a large U.S. City. *Environ Sci Technol* 46:12194–12202. doi:10.1021/es3011282
- Haas R, Auer H, Biermayr P (1998) The impact of consumer behavior on residential energy demand for space heating. *Energy Build* 27:195–205. doi:10.1016/S0378-7788(97)00034-0
- Heiple S, Sailor DJ (2008) Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles. *Energy Build* 40:1426–1436. doi:10.1016/j.enbuild.2008.01.005
- Hojjati B, Wade SH (2012) U.S. household energy consumption and intensity trends: a decomposition approach. *Energ Policy* 48:304–314. doi:10.1016/j.enpol.2012.05.024
- Holden E, Norland IT (2005) Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater Oslo region. *Urban Stud* 42: 2145–2166. doi:10.1080/00420980500332064
- Hsu A, Moffat AS, Weinfurter AJ, Schwartz JD (2015) Towards a new climate diplomacy. *Nat Clim Chang* 5: 501–503. doi:10.1038/nclimate2594
- Huang J, Akbari H, Rainer L, Ritschard R (1991) 481 prototypical commercial buildings for 20 urban market areas. Lawrence Berkeley Laboratory, Berkeley
- Hubacek K, Guan D, Barua A (2007) Changing lifestyles and consumption patterns in developing countries: a scenario analysis for China and India. *Futures* 39:1084–1096. doi:10.1016/j.futures.2007.03.010
- Hunt DRG, Gidman MI (1982) A national field survey of house temperatures. *Build Environ* 17:107–124. doi: 10.1016/0360-1323(82)90048-8
- IEA (2008) World energy outlook. Head of communication and information. Office International Energy Agency (IEA), Paris
- IEA (2009) Cities, towns & renewable energy: yes in my front yard. International Energy Agency (IEA), Paris
- Jenks M, Burton E, Williams K (1996) Compact cities and sustainability: an introduction. In: Jenks M, Burton E, Williams K (eds) *The compact city: a sustainable urban form?* E & FN Spon. Chapman & Hall, London
- Kennedy C, Steinberger J, Gasson B et al (2009) Greenhouse gas emissions from global cities. *Environ Sci Technol* 43:7297–7302. doi:10.1021/es900213p
- Kinneer EJ, Touma JS, Mason R et al (2004) Allocation of onroad mobile emissions to road segments for air toxics modeling in an urban area. *Transp Res Part Transp Environ* 9:139–150. doi:10.1016/j.trd.2003.09.003
- Koa Corporation (2011) Traffic signal management and synchronization project city of Salt Lake City. Koa Corporation, Orange, CA
- Lankao PR, Tribbia JL, Nychka D (2009) Testing theories to explore the drivers of cities' atmospheric emissions. *Ambio* 38:236–244
- Lauvaux T, Pannekoucke O, Sarrat C et al (2009) Structure of the transport uncertainty in mesoscale inversions of CO₂ sources and sinks using ensemble model simulations. *Biogeosciences* 6:1089–1102
- Lauvaux T, Miles NL, Deng A, et al. (2016) High resolution atmospheric inversion of urban CO₂ emissions during the dormant season of the Indianapolis Flux Experiment (INFLUX). (minor revision in Atmospheric Chemistry and Physics)
- Lin T, Yu Y, Bai X et al (2013) Greenhouse gas emissions accounting of urban residential consumption: a household survey based approach. *PLoS ONE* 8, e55642. doi:10.1371/journal.pone.0055642

- Lochner (2013) UTA network study: next tier program final report. Lochner, Salt Lake City
- Madireddy M, De Coensel B, Can A et al (2011) Assessment of the impact of speed limit reduction and traffic signal coordination on vehicle emissions using an integrated approach. *Transp Res Part Transp Environ* 16: 504–508. doi:10.1016/j.trd.2011.06.001
- McKain K, Wofsy SC, Nehrkorn T et al (2012) Assessment of ground-based atmospheric observations for verification of greenhouse gas emissions from an urban region. *Proc Natl Acad Sci* 109:8423–8428. doi:10.1073/pnas.1116645109
- Meehl GA, Washington WM, Collins WD et al (2005) How much more global warming and sea level rise? *Science* 307:1769–1772. doi:10.1126/science.1106663
- Mendoza D, Gumey KR, Geethakumar S et al (2013) Implications of uncertainty on regional CO2 mitigation policies for the U.S. onroad sector based on a high-resolution emissions estimate. *Energy Policy* 55:386–395. doi:10.1016/j.enpol.2012.12.027
- Newman DP, Kenworthy JR (1989) *Cities and automobile dependence: a sourcebook*. Gower Publishing, Brookfield
- Norman J, MacLean H, Kennedy C (2006) Comparing high and low residential density: life-cycle analysis of energy use and greenhouse gas emissions. *J Urban Plan Dev* 132:10–21. doi:10.1061/(ASCE)0733-9488(2006)132:1(10)
- NRC (2010) *Verifying greenhouse gas emissions: methods to support international climate agreements*. National Research Council (NRC). The National Academies Press, Washington
- O'Toole R (2008) Does rail transit save energy or reduce greenhouse gas emissions? *Cato Policy Anal* 615:1–24
- Oliveira EA, Andrade JS, Makse HA (2014) Large cities are less green. *Sci Rep*. doi:10.1038/srep04235
- Olivier JG, Janssens-Maenhout G, Muntean M, Peters J (2014) *Trends in global CO2 emissions: 2014 report*. JBL/JRC, The Hague
- Opower (2015) OPOWER. <https://opower.com/>. Accessed 17 Oct 2015
- Pachauri S (2004) An analysis of cross-sectional variations in total household energy requirements in India using micro survey data. *Energy Policy* 32:1723–1735. doi:10.1016/S0301-4215(03)00162-9
- Pataki DE, Bowling DR, Ehleringer JR, Zobitz JM (2006) High resolution atmospheric monitoring of urban carbon dioxide sources. *Geophys Res Lett* 33, L03813. doi:10.1029/2005GL024822
- Pataki DE, Xu T, Luo YQ, Ehleringer JR (2007) Inferring biogenic and anthropogenic carbon dioxide sources across an urban to rural gradient. *Oecologia* 152:307–322. doi:10.1007/s00442-006-0656-0
- Pataki DE, Emmi PC, Forster CB et al (2009) An integrated approach to improving fossil fuel emissions scenarios with urban ecosystem studies. *Ecol Complex* 6:1–14. doi:10.1016/j.ecocom.2008.09.003
- Petit JR, Jouzel J, Raynaud D et al (1999) Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica. *Nature* 399:429–436. doi:10.1038/20859
- Polyakov IV, Timokhov LA, Alexeev VA et al (2010) Arctic Ocean warming contributes to reduced polar ice cap. *J Phys Oceanogr* 40:2743–2756. doi:10.1175/2010JPO4339.1
- Poumanyong P, Kaneko S (2010) Does urbanization lead to less energy use and lower CO2 emissions? A cross-country analysis. *Ecol Econ* 70:434–444. doi:10.1016/j.ecolecon.2010.09.029
- Rahmstorf S (2007) A semi-empirical approach to projecting future sea-level rise. *Science* 315:368–370. doi:10.1126/science.1135456
- Rao P, Gurney K, Patarasuk R, et al. (2016) Spatio-temporal variations in onroad vehicle fossil fuel CO2 emissions in the Los Angeles Megacity (submitting to Environmental Pollution).
- Rayner PJ, Raupach MR, Paget M et al (2010) A new global gridded data set of CO2 emissions from fossil fuel combustion: methodology and evaluation. *J Geophys Res Atmos* 115, D19306. doi:10.1029/2009JD013439
- Rignot E, Velicogna I, van den Broeke MR et al (2011) Acceleration of the contribution of the Greenland and Antarctic ice sheets to sea level rise. *Geophys Res Lett* 38, L05503. doi:10.1029/2011GL046583
- RITA (2012) *National transportation atlas database*. Bureau of Transportation Statistics, US Department of Transportation. Research and Innovative Technology Administration (RITA). http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/national_transportation_atlas_database/index.html. Accessed 11 Jul 2012
- Salt Lake City (2010) *Salt Lake City: community carbon footprint*. Salt Lake City, UT
- Salt Lake City (2011) *Salt Lake City green: energy and transportation sustainability plan*. Salt Lake City, UT
- Salt Lake City (2014) *Plan Salt Lake: Existing conditions report*. Salt Lake City, UT
- Salt Lake City (2015) *Sustainable Salt Lake 2015*. Salt Lake City, UT
- Salt Lake City Transportation Division (2013) *Salt Lake City Traffic Studies (ESRI Geodatabase)*. Data provided by Salt Lake City Department of Information Management Services on 22 July 2013
- Salt Lake County Assessor's Office (2013) *Salt Lake County parcel data (ESRI Shapefile)*. Salt Lake County, UT
- Santamouris M, Kapsis K, Korres D et al (2007) On the relation between the energy and social characteristics of the residential sector. *Energy Build* 39:893–905. doi:10.1016/j.enbuild.2006.11.001

- Schuur EAG, Bockheim J, Canadell JG et al (2008) Vulnerability of permafrost carbon to climate change: implications for the global carbon cycle. *Bioscience* 58:701–714. doi:10.1641/B580807
- Seto KC, Fragkias M, Güneralp B, Reilly MK (2011) A meta-analysis of global urban land expansion. *PLoS ONE* 6, e23777. doi:10.1371/journal.pone.0023777
- Seto KC, Güneralp B, Hutya LR (2012) Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proc Natl Acad Sci* 109:16083–16088. doi:10.1073/pnas.1211658109
- Seto KC, Dhakal S, Bigio A et al (2014) Human settlements, infrastructure and spatial planning. In: Edenhofer O, Pichs-Madruga R, Sokona Y et al (eds) *Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge
- Shakun JD, Clark PU, He F et al (2012) Global warming preceded by increasing carbon dioxide concentrations during the last deglaciation. *Nature* 484:49–54. doi:10.1038/nature10915
- Smeds J, Wall M (2007) Enhanced energy conservation in houses through high performance design. *Energy Build* 39:273–278. doi:10.1016/j.enbuild.2006.07.003
- Solomon S, Plattner G-K, Knutti R, Friedlingstein P (2009) Irreversible climate change due to carbon dioxide emissions. *Proc Natl Acad Sci* 106:1704–1709. doi:10.1073/pnas.0812721106
- Stephens BB, Gurney KR, Tans PP et al (2007) Weak northern and strong tropical land carbon uptake from vertical profiles of atmospheric CO₂. *Science* 316:1732–1735. doi:10.1126/science.1137004
- Strong C, Stwertka C, Bowling DR et al (2011) Urban carbon dioxide cycles within the Salt Lake Valley: a multiple-box model validated by observations. *J Geophys Res Atmos* 116, D15307. doi:10.1029/2011JD015693
- Trenberth (2011) Changes in precipitation with climate change. *Clim Res* 47:123–138
- Turnbull JC, Sweeney C, Karion A et al (2015) Toward quantification and source sector identification of fossil fuel CO₂ emissions from an urban area: results from the INFLUX experiment. *J Geophys Res Atmos* 120: 292–312. doi:10.1002/2014JD022555
- UNFCCC (2015) Greenhouse Gas Inventory Data. http://unfccc.int/ghg_data/items/3800.php
- Vincent W, Jerram L (2006) The potential for bus rapid transit to reduce transportation-related CO₂ emissions. *J Public Transp*. doi:10.5038/2375-0901.9.3.12
- Walker IS, Meier AK (2008) Residential thermostats: comfort controls in California Homes. Lawrence Berkeley National Laboratory, Berkeley
- Wang R, Tao S, Ciais P et al (2013) High-resolution mapping of combustion processes and implications for CO₂ emissions. *Atmos Chem Phys* 13:5189–5203. doi:10.5194/acp-13-5189-2013
- Wheeler SM (2008) State and municipal climate change plans: the first generation. *J Am Plan Assoc* 74:481–496. doi:10.1080/01944360802377973
- WWF, ICLEI (2015) *Measuring up 2015: how local leadership can accelerate national climate goals*. World Wildlife Fund (WWF), Local Governments for Sustainability (ICLEI) USA, Washington
- York R, Rosa EA, Dietz T (2003) STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecol Econ* 46:351–365. doi:10.1016/S0921-8009(03)00188-5
- Zhao Y, Nielsen CP, McElroy MB (2012) China's CO₂ emissions estimated from the bottom up: recent trends, spatial distributions, and quantification of uncertainties. *Atmos Environ* 59:214–223. doi:10.1016/j.atmosenv.2012.05.027
- Zheng S, Wang R, Glaeser EL, Kahn ME (2010) The greenness of China: household carbon dioxide emissions and urban development. *J Econ Geogr* 10:q031. doi: 10.1093/jeg/lbq031
- Zhou Y, Gurney K (2010) A new methodology for quantifying on-site residential and commercial fossil fuel CO₂ emissions at the building spatial scale and hourly time scale. *Carbon Manag* 1:45–56. doi:10.4155/cmt.10.7