Spatial relationships of sector-specific fossil fuel CO_2 emissions in the United States

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[1] Quantification of the spatial distribution of sector-specific fossil fuel CO_2 emissions provides strategic information to public and private decision makers on climate change mitigation options and can provide critical constraints to carbon budget studies being performed at the national to urban scales. This study analyzes the spatial distribution and spatial drivers of total and sectoral fossil fuel CO_2 emissions at the state and county levels in the United States. The spatial patterns of absolute versus per capita fossil fuel CO_2 emissions differ substantially and these differences are sector-specific. Area-based sources such as those in the residential and commercial sectors are driven by a combination of population and surface temperature with per capita emissions largest in the northern latitudes and continental interior. Emission sources associated with large individual manufacturing or electricity producing facilities are heterogeneously distributed in both absolute and per capita metrics. The relationship between surface temperature and sectoral emissions suggests that the increased electricity consumption due to space cooling requirements under a warmer climate may outweigh the savings generated by lessened space heating. Spatial cluster analysis of fossil fuel CO_2 emissions confirms that counties with high (low) CO_2 emissions tend to be clustered close to other counties with high (low) CO_2 emissions and some of the spatial clustering extends to multistate spatial domains. This is particularly true for the residential and transportation sectors, suggesting that emissions mitigation policy might best be approached from the regional or multistate perspective. Our findings underscore the potential for geographically focused, sector-specific emissions mitigation strategies and the importance of accurate spatial distribution of emitting sources when combined with atmospheric monitoring via aircraft, satellite and in situ measurements.

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1. Introduction

[2] CO_2 emissions from fossil fuel combustion and cement manufacture are one of the principal drivers of climate change [*Denman et al.*, 2007]. As the number of in situ CO_2 and carbon flux measurements increases and as remote sensing atmospheric CO_2 observational platforms measure concentrations at scales of 100 km^2, bottom-up inventories of carbon exchange must quantify fluxes at commensurate space/time scales [*Gurney et al.*, 2005; *Gurney*, 2007]. A key goal of the North American Carbon Program is an improved understanding of the complete exchange of carbon between the land, atmosphere and coastal ocean [*Wofsy and Harriss*, 2002]. Hence, particular emphasis has been placed on improving inventories and atmospheric observations over the North American domain.

[3] Similar interest has arisen regarding greenhouse gas mitigation efforts. Because of the dominance of fossil fuel CO_2 emissions as a driver of anthropogenic climate change, understanding the spatial pattern of these emissions, especially by economic sector, is essential in order to better inform greenhouse gas regulation and mitigation decisions [*Parshall et al.*, 2009]. As CO_2 emissions are not a spatially random process, this understanding benefits from a spatially explicit view. Furthermore, because emissions are driven by distinctly different processes with unique space and time signatures when analyzed in terms of economic sector, the ability to disaggregate total fossil fuel CO_2 emissions by economic sector and subsector offers greater potential for optimal mitigation decisions and strategic planning than analysis based on total CO_2 emissions. Finally, detail in space and by economic driver offers a deeper insight into the relationships between emissions and the underlying socioeconomic and sociodemographic driving processes, allowing mitigation strategies to incorporate "upstream" as opposed to "end of pipe" approaches [*Aldy*, 2005; *Wu et al.*, 2005].

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[4] Prior to the availability of results from the "Vulcan Project," fossil fuel CO_2 emissions had been resolved globally, at the $1° \times 1°$ spatial scale based on spatial proxies such as population density, and most commonly at an annual time scale [*Andres et al.*, 1996; *Olivier et al.*, 1999; A. L. Brenkert, Carbon dioxide emission estimates from fossil-fuel burning, hydraulic cement production, and gas flaring for 1995 on a one degree grid cell basis, Oak Ridge National Laboratory, Oak Ridge, Tennessee, 1998, available at http://cdiac.esd.ornl.gov/ndps/ndp058a.html]. Within the U.S. domain, emissions had been quantified at the state level by fuel category or economic sector [*Blasing et al.*, 2005a; *Gregg et al.*, 2009; Energy Information Administration, State energy data system (SEDS), 2009, available at http://www.eia.doe.gov/emeu/states/_seds.html]. Some studies had analyzed point sources but focused on a single sector or sector segment [*Ackerman and Sundquist*, 2008; *Pétron et al.*, 2008]. The population-based inventories were useful in global studies but there were significant limitations to their use as research began to focus on finer scales, such as the U.S. state or county level. For example, at fine spatial scales, population density is a poor predictor of large point sources such as power plants which are often not collocated with population centers [*Blasing et al.*, 2005b]. Furthermore, the population-based inventories were not disaggregated by economic sector which is often an important source of evaluation and an important categorization for policymaking efforts.

[5] The Vulcan Project (http://www.purdue.edu/eas/carbon/vulcan/) provided the first U.S., process-driven, fuel-specific, fossil fuel CO_2 emissions inventory, quantified at scales finer than 10 km/hourly for the year 2002 [*Gurney et al.*, 2009]. This data product includes detail on combustion technology and forty-eight fuel types through all sectors of the U.S. economy. The Vulcan inventory is built from decades of local/regional air pollution monitoring and complements these data with census, traffic, and digital road data sets. These data sets are processed by the Vulcan inventory method at both the "native" resolution (geocoded points, county, road, etc) and on a regularized grid to facilitate atmospheric modeling and climate studies.

[6] In this study, we analyze the Vulcan inventory fossil fuel CO_2 emissions from the spatial perspective emphasizing economic sector disaggregation at the U.S. state and county spatial scales. We analyze the per capita statistical distribution, spatial and environmental gradients, and the spatial clustering of fossil fuel CO_2 emissions using a spatial statistical approach. Our analysis isolates key spatial attributes of CO_2 emissions providing a basis for interpreting observed atmospheric CO_2 and designing place-based emissions mitigation policy.

2. Methods

2.1. Sector-Specific CO_2 Emissions

[7] The total CO_2 emissions (onsite) in the Vulcan inventory are based on data that are reported as a combination of point, area, and linear source classifications. These data classes are ultimately assigned to the following economic sectors: residential, commercial, industrial, electricity production, onroad, nonroad (such as trains, boats, snowmobiles, and lawnmowers), aircraft, and cement production (calcination) [*Gurney et al.*, 2009]. Each of these is a combination of more than one data source classification, but the percentage varies by sector [*Gurney et al.*, 2009]. For example, the commercial sector is derived from both area and point source reporting whereas the industrial sector is derived almost entirely from point sources. This study focuses on the total onsite fossil fuel combustion CO_2 emissions with the following sectoral breakdown: residential, commercial, industrial, electricity production, and transportation (combination of onroad, nonroad, and aircraft) sectors (note we do not include cement production in the current analysis). The total 2002 CO_2 emissions from these sectors in the U.S. are 1583 Mt C [*Gurney et al.*, 2009].

[8] The residential and commercial CO_2 emissions are predominantly derived from area sources which represent diffuse emissions within an individual U.S. county. The industrial CO_2 emissions are dominated by point stationary emitting sources identified to a geocoded location and comprise entities in which emissions exit through a stack or identifiable exhaust feature [*U.S. Environmental Protection Agency*, 2006]. The airport source includes emissions associated with geocoded airport locations and represents the takeoff/landing cycle (emissions below 3000 feet), taxiing, idling and related aircraft activities on an annual basis [*U.S. Environmental Protection Agency*, 2005a]. The point, nonpoint, and airport data files come from the Environmental Protection Agency's (EPA) National Emissions Inventory (NEI) for the year 2002 [*U.S. Environmental Protection Agency*, 2005b].

[9] In all three of these data files (point, nonpoint, and airport sources) we utilize the reported CO emissions and CO and CO_2 emission factors. These factors are specific to the combustion process and the fuels tracked in the Vulcan system. CO emission factors are often supplied in the incoming data sets. Emission factors for CO_2 are based on the fuel carbon content and assume a gross calorific value or high heating value. Only emissions associated with fuel combustion are included in the Vulcan estimates. The basic process by which CO_2 emissions are created is as follows:

$$E_{n,f}^{CO_2} = \frac{E_{n,f}^{g}}{EF_{n,f}^{g}} EF_{n,f}^{CO_2} \times Ox\% \tag{1}$$

where $E_{n,f}^{CO_2}$ are the CO_2 emissions for process n (e.g., industrial 10 MMBTU boiler, industrial gasoline reciprocating turbine) and fuel type f (e.g., natural gas or bituminous coal); $E_{n,f}^{g}$ are the equivalent amount of uncontrolled criteria pollutant emissions g (CO) for process n and fuel type f; $EF_{n,f}^{g}$ is the emission factor associated with the criteria pollutant g for process n and fuel type f; $EF_{n,f}^{CO_2}$ is the CO_2 emission factor for process n and fuel type f and $Ox\%$ is the oxidation factor (100% for natural gas and 99% for coal and oil).

[10] Because of the reliability of direct CO_2 monitoring and the need for fine time resolution data, we utilize observed CO_2 emissions available at electrical generating units (EGUs) (U.S. Environmental Protection Agency, Clean air markets: Data and maps, Clean Air Markets Division, EPA, Washington, D. C., 2008, http://camddataandmaps.epa.gov/gdm/). These data contain a large number of facilities that utilize Emission Tracking System/Continuous Emissions Monitoring

systems (ETS/CEMs), widely considered the most accurate for CO_2 emissions estimation at these facilities [*Pétron et al.*, 2008].

[11] The onroad transportation emissions are based on a combination of county-level data and standard internal combustion engine stochiometry. The county-level data come from the National Mobile Inventory Model (NMIM) County Database (NCD) for 2002 which quantifies the vehicle miles traveled in a county by month, specific to vehicle class and road type [*U.S. Environmental Protection Agency*, 2005c]. The Mobile6.2 combustion emissions model is used to generate CO_2 emission factors on a per mile basis given inputs such as fleet information, temperature, fuel type, and vehicle speed [*U.S. Environmental Protection Agency*, 2001]. Nonroad emissions are structured similarly to the onroad mobile emissions data and consist of mobile sources that do not travel on designated roadways [*U.S. Environmental Protection Agency*, 2005a]. The Aero2K aircraft CO_2 emissions inventory is directly used to estimate aircraft emissions beyond the takeoff/landing cycle emissions captured in the NEI airport database [*Eyers et al.*, 2004].

[12] Further details regarding the Vulcan methodology can be found in the work of *Gurney et al.* [2009] and in the detailed Vulcan online methodology documentation (http://www.purdue.edu/eas/carbon/vulcan/Vulcan.documentation.v1.1.pdf).

[13] We use two different spatially resolved outputs from the Vulcan results: county-level emissions (which are aggregated to state level where needed) and emissions transferred to a 10 km × 10 km regular spatial grid. All analysis utilizes the county results except for the exploration of geographic and environmental impact (section 3.4).

[14] Population statistics similarly utilize two different population data sets. For use with county-level emissions, we use the 2002 U.S. Census county-level population estimates (http://www.census.gov/popest/counties/counties.html). For use with the 10 km × 10 km gridded emissions, we use gridded population for the year 2000 available at 30 arc-second resolution (~1 km) from the Socioeconomic Data and Applications Center (SEDAC) Project (http://sedac.ciesin.columbia.edu/usgrid).

2.2. Probability Distribution

[15] A succinct method by which to gain an understanding of the overall characteristics of the spatially resolved per capita fossil fuel CO_2 emissions is through the use of probability distributions. Here, we analyze a related quantity, the cumulative probability distribution (*CPD*), which is the probability that X is less than or equal to a given value x:

$$CPD(x) = Prob(X \leq x) \tag{2}$$

With the increase of x, *CPD* increases from 0 to 1. For a data set with n values x_i, the *CPD* can be calculated as $CPD(x_i) = i/n$ by sorting x_i into increasing order, where i is the sorted index [*Raupach et al.*, 2010].

2.3. Geographic Patterns

[16] In order to study the impact of sector-specific, environmental gradients on the national CO_2 emissions, we separated the U.S. into different geographic zones along longitude, latitude, elevation, heating degree day (HDD), and cooling degree day (CDD). We classified six zones based on longitude, five zones based on latitude, ten zones based on elevation, nine zones based on HDD, and eight zones based on CDD. We used the 1961–1990 annual mean total heating and cooling degree day from the *National Climatic Data Center* [2002]. The per capita CO_2 emissions in each of the defined zones were calculated as follows.

$$CP_i^m = \frac{\sum_j C_{i,j}^m}{\sum_j P_{i,j}} \tag{3}$$

where CP_i is the per capita CO_2 emissions in each zone i, j is the pixel number in each zone, C is the CO_2 emissions, P is population, and m is the economic sector.

2.4. Spatial Clustering

[17] Compared with visual examination of thematic maps, statistical cluster analysis is a more objective metric when analyzing nonrandom spatial patterns. Exploratory spatial data analysis (ESDA) method was used to study the spatial patterns of absolute and per capita CO_2 emissions in each economic sector. A global Moran's I test, a univariate statistic which is a measure of spatial autocorrelation, was performed to assess whether the pattern of sector-specified CO_2 emissions has an average tendency to cluster in space [*Anselin et al.*, 2004]. The global measure of Moran's I is defined as:

$$I = \frac{N}{\sum_i \sum_j W_{ij}} \frac{\sum_i \sum_j W_{ij}(X_i - \mu)(X_j - \mu)}{\sum_i (X_i - \mu)^2} \tag{4}$$

Where N is the number of spatial units, W_{ij} is the row-standardized contiguity matrix, X_i is the absolute or per capita CO_2 emissions in area i, X_j is the absolute or per capita CO_2 emissions in area j, and μ is the average level of absolute or per capita CO_2 emissions. Neighbors used to build the contiguity-based weights were designed based on the first-order rook matrix which defines a location's neighbors as those areas with shared borders [*Anselin et al.*, 2004].

[18] With the tendency for spatial clustering quantified, a local indicator was used to identify the location of clusters. Local indicators of spatial association (LISA) provides information relating to the location of spatial clusters and the types of spatial correlation [*Anselin*, 1995; *Anselin et al.*, 2004, 2006; *Borden and Cutter*, 2008; *Loughnan et al.*, 2008; *Franczyk and Chang*, 2009]. LISA provides more information about the magnitude of spatial autocorrelation at the local level in addition to the global scale, especially for spatially heterogeneous variables. The local measure of Moran's I, LISA, is defined as:

$$I = \frac{N(X_i - \mu)}{\sum_i (X_i - \mu)^2} \sum_j W_{ij}(X_j - \mu) \tag{5}$$

Here we define clusters of "high-high" emissions as spatially coherent clusters of large magnitude fossil fuel CO_2

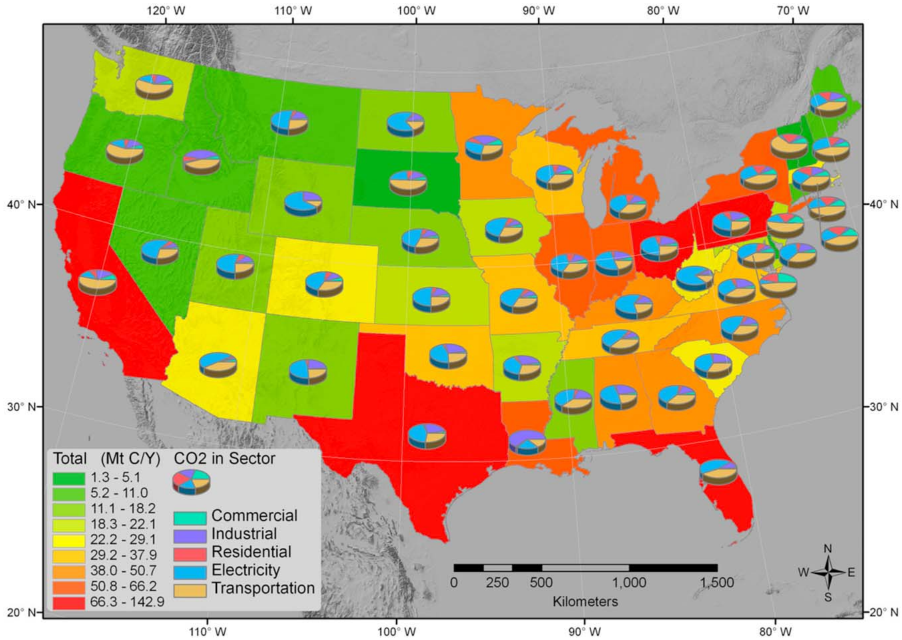

Figure 1. Total and sector-specific contiguous U.S. fossil fuel CO_2 emissions at the state level for the year 2002.

emissions, and cluster of "low-low" emissions as spatially coherent clusters of low-values fossil fuel CO_2 emissions.

3. Results and Discussion

3.1. Top Ten State-Level Emitters

[19] Figure 1 shows the spatial distribution of CO_2 emissions and its sectoral breakdown at the state level. The results not only demonstrate the spatial variation of total CO_2 emissions, but also the sectoral variation in each state. Electricity production in the middle of the U.S. is the largest proportion of the total CO_2 emissions, while transportation dominates in the coastal states. The largest emitters overall are a combination of those with large populations and/or significant industrial activity.

[20] Tables 1 and 2 present the top ten fossil fuel CO_2 emitting states sorted by magnitude within each economic sector in absolute and per capita units, respectively. In absolute terms, the states of Texas and California are consistently in the top positions across the economic sectors. The sector for which Texas does not occupy a position within the top five is the residential sector. This is likely due to the limited winter demand for space heating, the dominant source of onsite residential CO_2 emissions in colder locales. Similarly, California does not occupy a position in the top five for the electricity production sector. This is likely due to the fact that a significant share (>50%) of California electricity consumption is generated by nonfossil fuel sources (*Energy Information Administration*, 2009).

[21] Examination of the top emitters on a per capita basis shows a greater mix of states occupying the top positions. States with low populations combined with more northern latitudes, energy-intensive industry or electricity production determine the top positions.

3.2. County-Level Spatial Patterns

[22] The spatial patterns of the absolute and per capita total CO_2 emissions at the county spatial scale are shown in

Table 1. The Top Ten Absolute Vulcan 2002 Fossil Fuel CO_2 Emitting States by Magnitude Within Each Economic Sector[a]

Total		Residential		Commercial		Industrial		Electricity Production		Transportation	
Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State
142.88	TX	9.71	NY	6.4	CA	37.48	LA	60.97	TX	50.68	CA
99.66	CA	7.67	CA	4.38	NY	36.22	TX	33.48	OH	39.07	TX
75.44	OH	7.39	IL	4.22	PA	18.6	CA	33.36	FL	31.56	FL
73.78	FL	6.62	PA	3.72	IL	14.71	PA	32.18	IN	22.84	NY
71.31	PA	6.05	OH	3.61	TX	14.27	OH	27.6	PA	21.87	IL
66.21	IL	5.71	MI	2.93	MN	12.63	IN	25.14	IL	18.98	OH
62.63	IN	4.59	NJ	2.76	IN	11.9	MN	24.86	KY	18.65	GA
61.4	LA	4.42	MA	2.66	OH	11.53	AL	22.86	WV	18.16	PA
53.66	NY	3.01	TX	2.64	NJ	8.59	OK	21.72	AL	18.12	MI
51.76	MI	2.73	WI	2.24	MI	8.1	IL	20.84	GA	14.7	NC

[a]Units: million tonnes of carbon per year.

Table 2. The Top Ten per Capita Vulcan 2002 Fossil Fuel CO_2 Emitting States by Magnitude Within Each Economic Sector[a]

Total		Residential		Commercial		Industrial		Electricity Production		Transportation	
Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State	Magnitude	State
36.69	WY	0.81	ME	1.03	AK	8.39	LA	24.05	AK	4.08	WY
21.11	ND	0.77	VT	0.58	MN	8.33	WY	14.44	WY	3.34	NM
16.17	WV	0.69	MA	0.56	DC	7.33	AK	12.71	ND	3.28	VT
14.29	AK	0.65	AK	0.51	WY	2.58	AL[b]	6.08	SD	2.75	OK
13.75	LA	0.64	CT	0.45	IN	2.47	OK	5.24	MT	2.56	GA
10.19	IN	0.63	RI	0.44	ND	2.40	ND	5.20	NE	2.33	TN
10.17	AL[b]	0.60	NH	0.38	WI	2.37	MN	4.86	OK	2.32	MO
9.82	KY	0.59	UT	0.34	PA	2.12	NM	4.58	NM	2.29	MS
9.71	MT	0.59	IL	0.34	WV	2.12	AR	4.13	VT	2.29	AL
9.59	NM	0.57	MI	0.34	RI	2.06	IN	4.12	AL	2.22	MT

[a]Units: tonnes of carbon per year per person.
[b]The underlying data reporting for Alabama has acknowledged biases. These have been corrected where possible [see *Gurney et al.*, 2009].

Figure 2. Large total (Figure 2a) absolute CO_2 emissions occur in Florida, the upper Midwest population centers, the Southwest, west coast population centers, the southern Rocky Mountain region, and the "BosNYWash" corridor of the east coast. On a per capita basis, emissions have a nearly inverse relationship to the absolute spatial distribution in which larger emissions occur in the Western Plains and Rocky Mountain regions coincident with lower population density. The influence of county size is notable in Figure 2. County sizes tend to be larger in the western half of the United States and hence must be considered when interpreting results at the county scale.

[23] Absolute residential CO_2 emissions (Figure 2b) are distinct from the total emissions pattern due to relatively greater emissions in the northeast, upper Midwest, west coast and southwest. When normalized by population, residential emissions are concentrated north of roughly 36°N latitude and east of the Rocky Mountains. These gradients reflect space heating needs driven by regions with more continental climate and, hence, longer, colder winters [*Energy Information Administration*, 2001]. The residential sector is strongly tied to population as absolute emissions are dominated by nonelectrical space heating in the Vulcan system [*Gurney et al.*, 2009].

[24] Absolute and per capita commercial CO_2 emissions (Figure 2c) show a pattern similar to that found in the residential sector but with less latitudinal dependence and a more scattered distribution of the larger per capita values. Because space heating constitutes a somewhat lower overall proportion of the total commercial fossil fuel energy use when compared to the residential sector, the spatial pattern appears less dependent upon climate conditions [*United States Department of Energy*, 2008].

[25] The per capita calculation in both the residential and commercial sectors reveals the weakness of aggregation at the county spatial scale. For example, some states show distinct boundary outlines when normalized by population (Utah, Illinois, and New York) and these are primarily due to the fact that building density varies significantly at scales below the county level. In the Vulcan data product produced at the 10 k × 10 km scale, these state outlines are eliminated due to the fact that residential and commercial emissions are distributed via census tract density of building area statistics [*Gurney et al.*, 2009].

[26] Large absolute industrial CO_2 emissions are distributed heterogeneously across the U.S. while centers of high per capita industrial CO_2 emissions show a slight concentration in particularly intense industrial regions with somewhat lower population density such as the Gulf Coast, the oil-producing/refining regions of Texas and Oklahoma, the upper Midwest and the Front Range of the Rocky Mountains (Figure 2d). Dominated by large power facilities, absolute and per capita electricity production CO_2 emissions show a similarly heterogeneous pattern across the U.S. due to the presence of large fossil fuel-based power production facilities in most regions and the presence of some of these facilities in counties with low population.

[27] High absolute transportation CO_2 emissions (Figure 2f) show a pattern similar to that found in the residential and commercial sectors while per capita transportation CO_2 emissions are clustered in the Western U.S. due to a combination of lower population density and longer average trip distance [*Peng and Lu*, 2007].

3.3. Probability Distributions of Per Capita Emissions

[28] The *CPD* of the sectoral per capita CO_2 emissions at the county level is shown in Figure 3. The distribution of the sectoral per capita CO_2 emissions can be described by three distinct groupings. In the case of the electricity production sector, the distribution shows per capita emissions which are spread over a wide distribution of values with the presence of both very small and very large per capita values. However, unlike the other economic sectors, emissions are present in a minority of the 3,141 counties in the U.S.; only 1,215 counties reported emissions from the electricity production sector. About 25 percent of those counties contain emissions less than 0.01 tonne C/person. In absolute terms, 75% of all electricity production CO_2 emissions are located in 233 counties, and 95% of the emissions are achieved after including 515 counties.

[29] Per capita transportation CO_2 emissions exhibit a relatively compressed distribution with values spanning the 1 to 4 tonne C/person range. This demonstrates the relatively homogeneous need for transportation on a per capita basis. The *CPD* of residential, commercial, and industrial CO_2 emissions can be considered a third distributional group with a range less compressed than the transportation sector but not as widely scattered as the electricity production

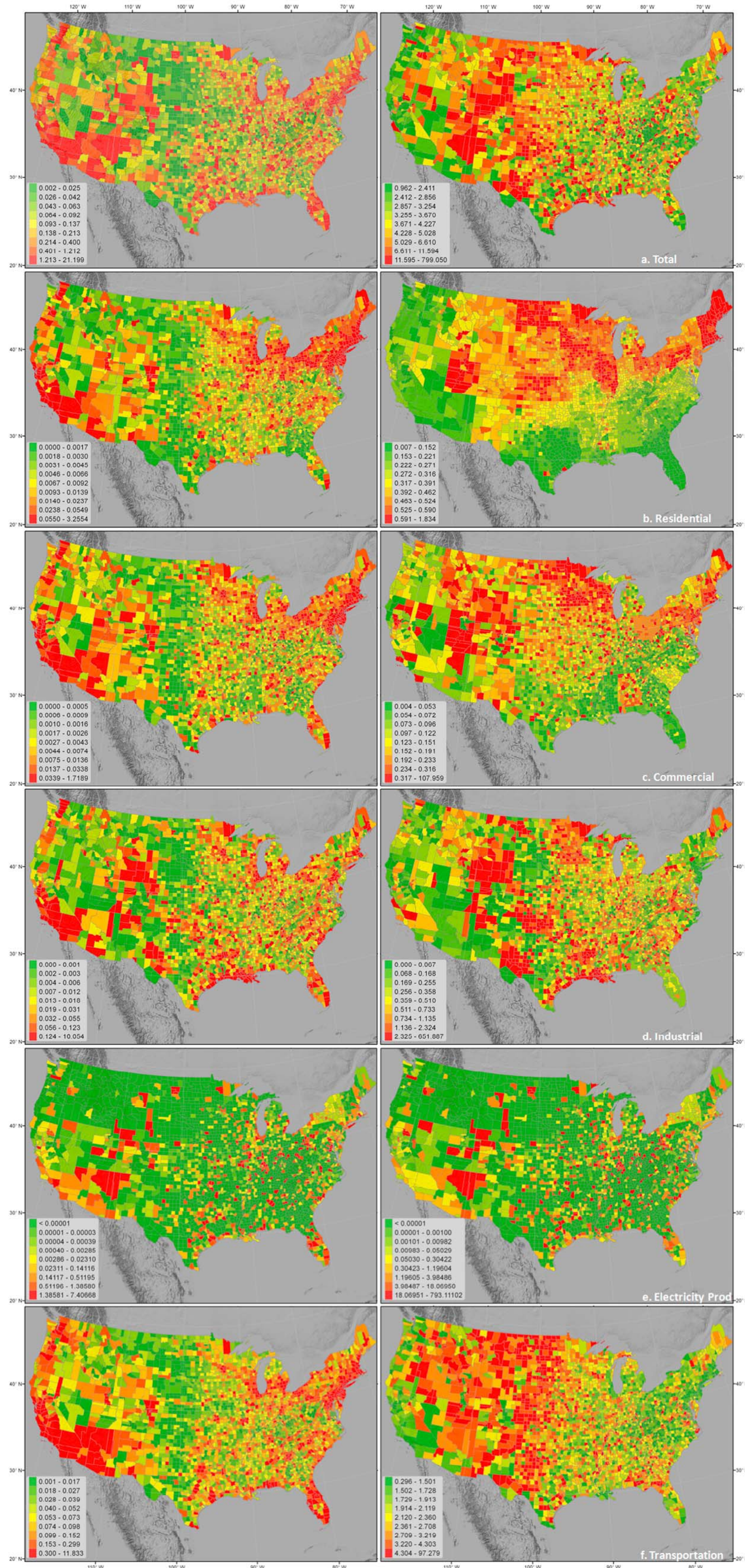

Figure 2. The (left) absolute (units: MtC/year) and (right) per capita (units: tonne C/year/person) CO_2 emissions at the county spatial scale from (a) all sources; (b) the residential sector; (c) the commercial sector; (d) the industrial sector; (e) the electricity production sector; and (f) the transportation sector.

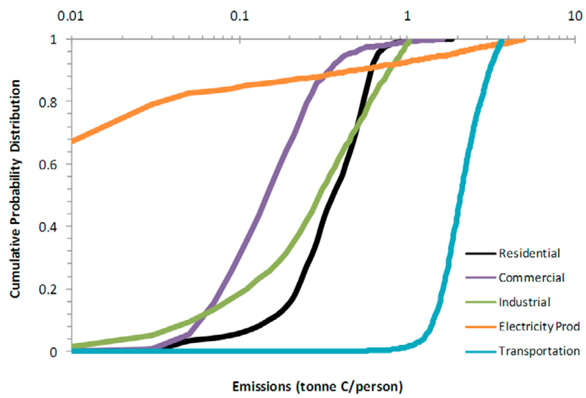

Figure 3. The cumulative probability distribution (CPD) of sectoral per capita CO_2 emissions at the county level. Per capita CO_2 emissions are on log scale.

sector. Of the three, industrial per capita CO_2 emissions span both the greatest range of values with a more even distribution, from very small to slightly greater than 1 tonne C/person. The commercial and residential per capita CO_2 emissions exhibit similar distributions but centered around different mean values of 0.15 and 0.4 tonne C/person, respectively.

3.4. Explanatory Variables

[30] In order to better understand the geographic and environmental influences on CO_2 emissions, we have binned per capita CO_2 emissions in each of the economic sectors according to three geographic and two climate variables: latitude, longitude, elevation, HDD, and CDD. We normalize the sector-specific, binned, per capita CO_2 emissions by subtracting the mean value and dividing by the standard deviation. Figure 4 shows the distribution of these sector-specific per capita CO_2 emissions as a function of the five variables.

[31] The per capita total CO_2 emissions are dominated by electricity production and hence, exhibit patterns similar to the per capita electricity production CO_2 emissions, as was noted in section 3.2 at the county spatial scale. The dependence of per capita electricity production CO_2 emissions is complicated by the fact that the geographic pattern is not expected to follow variables that drive electricity demand because of the potentially long distance that can separate production from demand, and that about 30% of electric power was generated from nonfossil fuel energy in 2002 [*Energy Information Administration*, 2003].

[32] The longitudinal distribution of per capita electricity production emissions is larger in the middle of the country with lesser amounts toward both coasts. Per capita electricity production emissions also decrease somewhat from south to north but increase with elevation. The increase in per capita emissions across the middle and southern portion of the country is in large part due to the location of large electricity production facilities in areas with low population density. This is further evidenced by states, such as Wyoming, Montana and North Dakota which are among the highest in-state coal producers [*Energy Information Administration*, 2009]. This results in high ratios of electric generation to

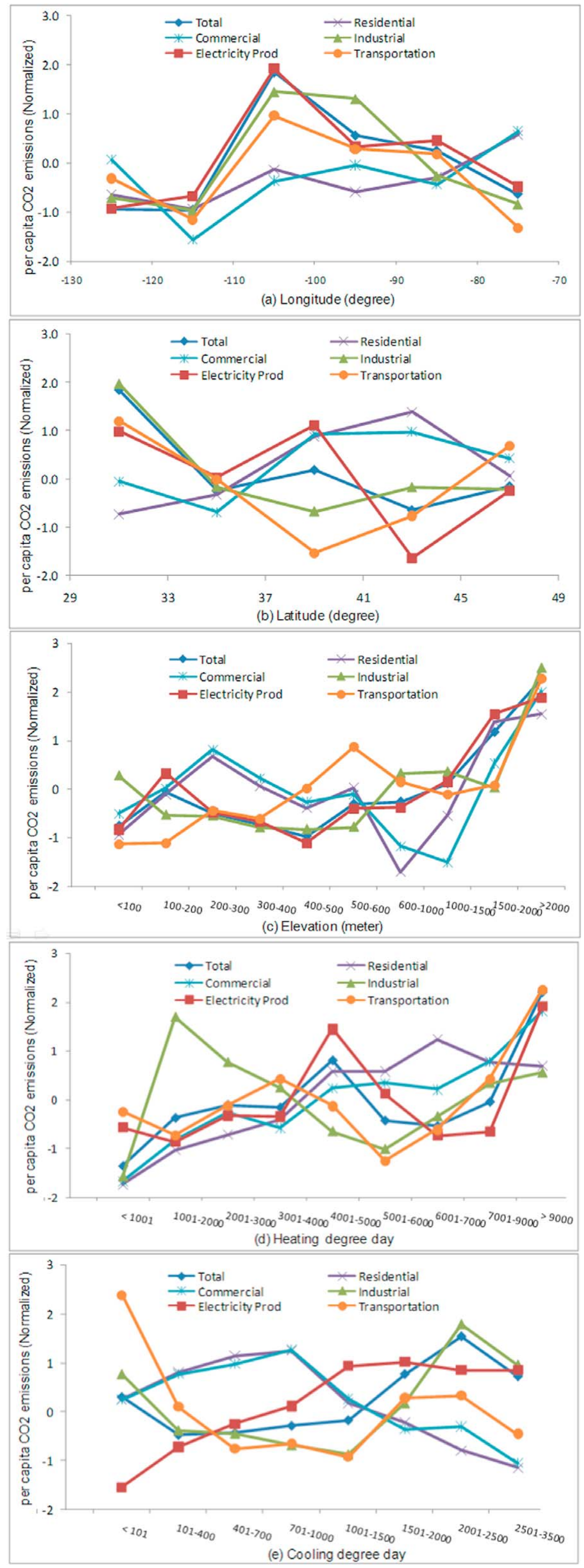

Figure 4. Spatial distribution of normalized per capita CO_2 emissions due to the total and the residential, commercial, industrial, electricity production, and transportation sectors as a function of (a) longitude; (b) latitude; (c) elevation; (d) heating degree day; and (e) cooling degree day.

in-state retail sales, implying that these states are net exporters of electricity [*Energy Information Administration*, 2008]. Finally, electricity production in the Midwestern and intermountain West is predominantly fueled by coal as opposed to less carbon-intensive energy sources such as hydro, prevalent on the west coast [*Energy Information Administration*, 2007]. Increasing per capita emissions with elevation is due to the fact that population density declines with elevation more dramatically than does electricity production. CO_2 emissions from electricity production show no consistent relationship to HDD, consistent with the fact that only about 8% of the space heating is directly driven by electricity (Energy Information Administration, Residential energy consumption survey, 2001, available at http://www.eia.doe.gov/emeu/recs/recs2001/ce_pdf/spaceheat/ce2-2c_construction2001.pdf). By contrast, there is a slight rise in per capita electricity production CO_2 emissions with increasing CDD. This is consistent with the expectation that electrical air-conditioning demand is higher in locales with a greater number of hot days [*Pétron et al.*, 2008]. Furthermore, we speculate that this may also be a collinear effect with the preponderance of coal-burning facilities in the Midwest which spans 1000 to 3000 cooling degree day range.

[33] The per capita residential and commercial CO_2 emissions share similar patterns for each of the independent variables and can be explained primarily by climate influences. Higher elevations and northern latitudes exhibit a greater number of HDD and hence greater space heating needs. The longitudinal dependence, with slightly higher values in the East and declining toward the West, may be partially due to the colder, more continental climate going from West to East and the fact that average house/building square footage also increases from West to East (Energy Information Administration, Residential energy consumption survey, 2005, available at http://www.eia.doe.gov/emeu/recs/recs2005/c&e/summary/pdf/tableus1part1.pdf). For example, average residential floor space per household based on 2005 sampling is smaller in the Pacific and Mountain census regions (1,708 and 1,951 ft^2, respectively) and larger in the East North Central and New England census regions (2,483 and 2,472 ft^2, respectively). Both residential and commercial per capita CO_2 emissions show a decline as the CDD increases. This is due to the fact that air conditioning needs are supplied through electricity, and hence, evident in the relationship between electricity production and CDD.

[34] The per capita industrial CO_2 emissions are larger in the interior versus coastal areas in the longitudinal direction while exhibiting a minimum in the 37°N to 41°N latitudinal bin. The larger values in the southern latitudes are due to the high-emitting oil production and refining of the Gulf coast region which are less labor-intensive as evidenced by their higher ratio of receipts per paid employee (http://www.census.gov) than other industrial sectors. The per capita industrial CO_2 emissions have little dependence upon elevation with a shift in values at approximately 600 m, above which are mainly mountain states. The per capita industrial CO_2 emissions exhibit a complicated relationship to HDD and CDD with a minimum in the center of the HDD and CDD numerical spans and this may be collinear with the underlying geographic distribution. Furthermore, the use of a per capita normalization in the industrial sector (like the electricity sector to a somewhat lesser degree) is complicated by a number of factors. The amount of labor required to support industrial activities varies and that variation depends upon broad industrial classifications which, in turn, have geographic relationships. For example, the top coal producers, West Virginia, Kentucky and Wyoming (*Energy Information Administration*, 2009), are among the states with the highest GDP in the mining industrial category (http://www.bea.gov/regional/gsp).

[35] The longitudinal dependence of per capita transportation emissions exhibit a maximum in the continental interior corresponding to the ridge of large values running west to east along the Mountain and intermountain West. This is driven, in large measure, by the presence of large coast population centers with high population density and small trip distance values [*Puentes and Tomer*, 2008]. By contrast, the latitudinal distribution of per capita transportation emissions has a minimum value in the middle of the country. The relationship with elevation correlates with the region of sparse population and high trip distance and further corresponds to lower road densities noted by the National Highway Planning Network data (http://www.fhwa.dot.gov/planning/nhpn/).

[36] Increases in per capita transportation CO_2 emissions with elevation are due to greater trip distances in predominantly rural, high-elevation locales. The relationship between per capita transportation emissions and HDD exhibits maxima at values ranging from 2000 to 4000 and at values greater than 7000. The relationship is likely collinear with geography, particularly the increasing per capita transportation emissions at the higher HDD values, which corresponds to the rural, high trip distance mountain and intermountain West. Similarly, the relationship between per capita transportation emissions and CDD exhibits some collinearity with geography (the lowest CDD values correspond to the cold mountain/inter mountain west) though research supports lessening vehicle efficiency at higher temperatures due to increased air conditioner use. Studies indicate that running the air conditioning in a passenger car reduces fuel efficiency by approximately 12% at highway speeds [*Parker*, 2005; *Climate Change Science Program*, 2007].

[37] The relationship between the sectoral per capita emissions and the CDD/HDD values has implications for how energy demand and emissions will respond to climate change. Though spatial gradients are not a perfect substitute for temporal behavior, the spatial relationships are informative. For the HDD metric, both the residential and commercial per capita emissions show a reasonably linear response. In the residential and commercial sectors, binned HDD values explain 88% and 86% of the variation in per capita carbon emissions. Furthermore, the relationship suggests a decline of 0.07 and 0.03 kg C/person per unit of HDD decline in the residential and commercial sectors, respectively, a reflection of the lessened need for space heating as HDD values decline over space.

[38] For the CDD metric, the relationship is most pronounced for emissions in the electricity production sector (explained variance of 68%). This relationship suggests that an increase in one unit of CDD would be accompanied by 0.57 kg of carbon per person. This exceeds the incremental residential and commercial space heating emissions decline

Table 3. The Global Moran's I for Absolute and per Capita Fossil Fuel CO_2 Emissions in Each Economic Sector and Total Source[a]

CO_2 Emissions	Moran's I (Absolute)	Moran's I (per Capita)
Total	0.23 (0.001)	0.13 (0.001)
Residential	0.43 (0.001)	0.82 (0.001)
Commercial	0.25 (0.001)	0.00 (0.1)
Industrial	0.10 (0.001)	0.03 (0.02)
Electricity Prod	0.08 (0.001)	0.13 (0.001)
Transportation	0.34 (0.001)	0.15 (0.001)

[a]Statistical significance is provided in parentheses.

due to warmer temperatures by over a factor of five. Some of this is explained by the carbon intensiveness of electricity production versus space heating. However, even if one assumed that all electricity production was based on coal and all space heating was based solely on natural gas, the ratio of carbon intensity would suggest a factor of two. Hence, it would appear that per capita electricity production CO_2 emissions are far more sensitive to external temperature than residential and commercial per capita CO_2 emissions. This stands in stark contrast to studies that have suggested future warming would be accompanied by savings in space heating needs that nearly offset the requirements of increased cooling [*Hadley et al.*, 2006].

3.5. Spatial Clustering

[39] To objectively explore the spatial patterns of fossil fuel CO_2 emissions produced by the Vulcan inventory, a null hypothesis, implying random spatial distribution, was tested via spatial autocorrelation using a Global Moran's I. The results for absolute and per capita CO_2 emissions in each sector are summarized in Table 3. The statistical significance of the spatial clustering was computed using a permutation approach with 9999 permutations [*Anselin et al.*, 2004]. The results indicate statistically significant positive spatial autocorrelation for the absolute and per capita CO_2 emissions in all sectors except for the per capita emissions in the commercial sector. A large positive value indicates that similarly valued emissions are highly clustered in space.

[40] The positive autocorrelation of per capita CO_2 emissions in each sector is lower than the absolute value except for the residential and electricity production sectors. This is due to the clustering effect of population and the associated emissions in large population centers. For example, the global Moran's I coefficient for transportation CO_2 emissions decreases from 0.34 to 0.15 when normalized by population.

[41] The largest spatial autocorrelation value is present in the residential sector with a global Moran's I coefficient of 0.43 and 0.82 for the absolute and per capita values, respectively. This is consistent with the evidence that residential emissions are dominated by space heating and space heating is driven by local climate, itself a positively autocorrelated variable [*Tan et al.*, 2005]. Normalization by population heightens this effect by focusing on colder areas with lower population density. The result is high clustering in the upper Midwest, New England, and the Rocky Mountains. The low Moran's I coefficients for the industrial sector and electricity production indicates a more random distribution of emissions. This is not entirely surprising as the emissions in these two sectors are dominated by point sources which are often isolated and in low population density locales [*Gurney et al.*, 2009].

[42] Figure 5 presents the sector-specific LISA values (denoted as "high-high" and "low-low") for the absolute and per capita CO_2 emissions.

[43] The clusters of low-low absolute CO_2 emissions show similar patterns across all the sectors except for electricity production in which the low-low clustering throughout the western Plains region is absent. This owes in part to the presence of large electricity production facilities in relatively remote portions of the West and Southwest United States [*Gurney et al.*, 2009]. The extent of these low-low clusters varies in each economic sector, however. The low-low absolute CO_2 emissions in transportation sector have the greatest spatial extent compared to other sectors. The clusters of low-low absolute industrial CO_2 emissions are distributed somewhat more heterogeneously than other economic sectors. The high-high clusters of absolute CO_2 emissions are less extensive than the low-low clusters across all sectors. Aside from electricity production and the industrial sector, the clusters of high-high absolute CO_2 emissions are mainly distributed throughout the high population urban corridors. As with the low-low clustering, the high-high clustering for electricity production and the industrial emissions are scattered and limited in spatial extent. This, once again, highlights the disaggregated nature of these point source facilities.

[44] Normalization by population causes a shift in which the low-low cluster moves from predominantly inland locations to more coastal regions across all sectors. The exception to this pattern is electricity production which shows only a minor change when normalized by population. The spatial extent of these clusters tends to decrease except for the residential sector. The residential per capita CO_2 emissions, by contrast, show large low-low clusters throughout the coastal U.S., occurring along the west coast, the Southwest, the Gulf coast, and coastal Southeast. The areas of low-low per capita commercial CO_2 emissions are next in magnitude, and share much of the pattern of the residential per capita emissions except that the western and southwest maxima do not occur. These low-low clusters are coincident with milder marine-influence climates, requiring less extreme wintertime interior heating.

[45] The high-high clusters of per capita CO_2 emissions are most pronounced for the residential and transportation sectors where they tend to occupy inland areas, especially in the case of the transportation sector. The high-high clusters of per capita CO_2 emissions in the residential sector are the largest and most spatially coherent, and they mainly occur in New England, the Middle West, Utah, and Kansas. The low-low and high-high spatial clustering of per capita electricity CO_2 emissions is small compared to other sectors. Owing to the fact that they dominate the total emissions, this pattern tends to drive the spatial clustering in Figure 5a.

4. Conclusions

[46] The fossil fuel CO_2 emissions inventory developed by the Vulcan Project provides a sector-specific high resolution view of anthropogenic CO_2 emissions in the United

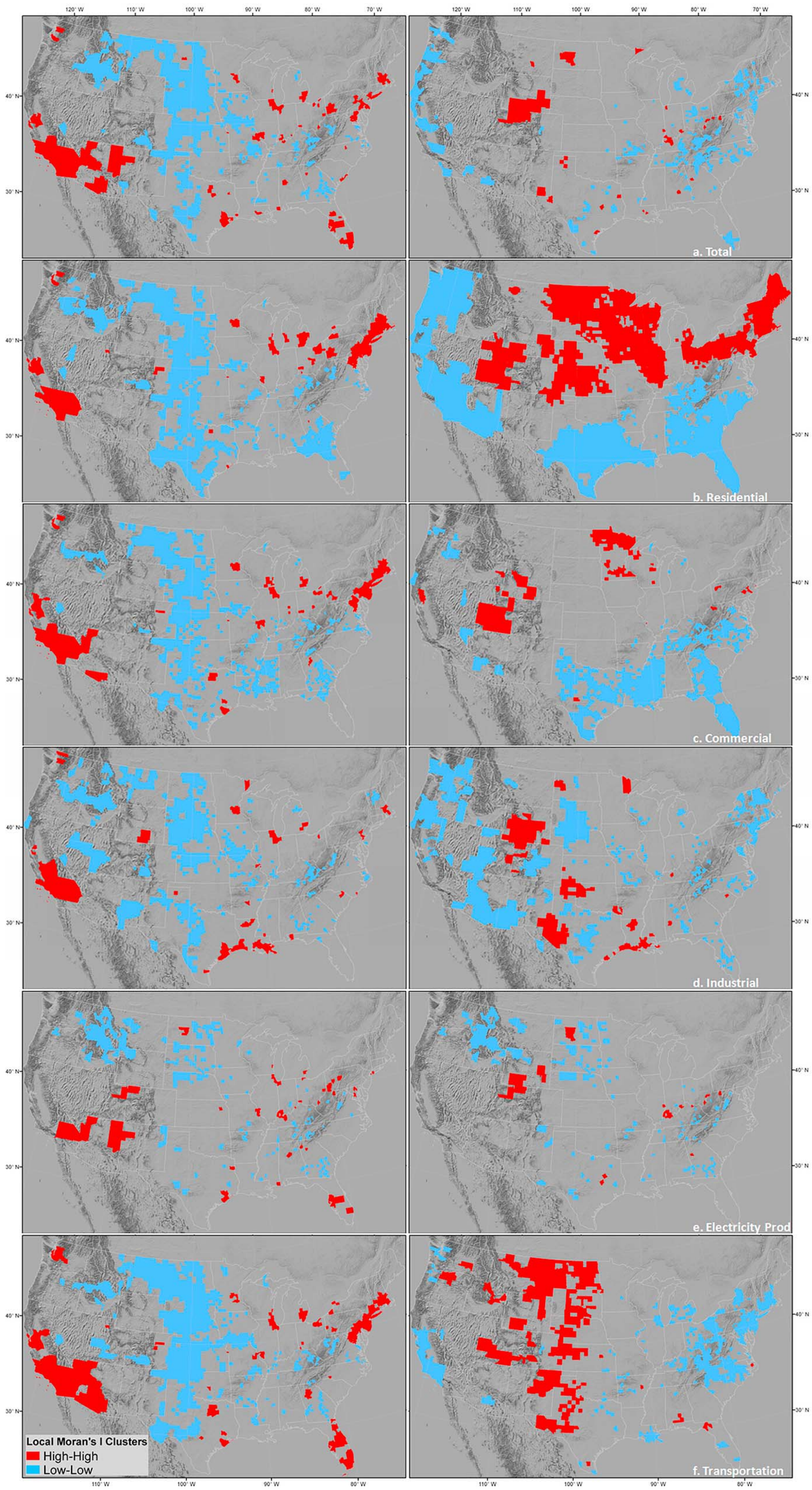

Figure 5. LISA cluster maps for the (left) absolute and (right) per capita CO_2 emissions at the county spatial scale from (a) total sources; (b) the residential sector; (c) the commercial sector; (d) the industrial sector; (e) the electricity production sector; and (f) the transportation sector.

States. The work presented here analyzes the spatial patterns of the absolute and per capita Vulcan CO_2 emissions and finds consistency with research at coarser scales that highlights the impacts of environment and place on CO_2 emissions [*Coondoo and Dinda*, 2008]. Through the analysis presented here, the following conclusions can be drawn.

[47] 1. The spatial patterns of absolute versus per capita fossil fuel CO_2 emissions differ substantially and these differences are sector-specific. This is especially true of the residential and transportation sectors where absolute emissions tend to be highest in population centers. Per capita emissions in the residential sector, by contrast, tend to be highest in more continental/northern locations. Per capita transportation emissions are highest in regions with low population density and high mean travel distance. At the state-level, populous, industrial-active states such as California and Texas tend to occupy the top emitting positions in terms of absolute emissions.

[48] 2. The statistical distribution of the per capita emissions shows the narrowest distribution for the transportation sector with values ranging from 1 to 4 tonnes C/person. Electricity production exhibits the widest distribution with values ranging from 0.001 tonnes C/person to values greater than 100 tonnes C/person.

[49] 3. The HDD is a critical determinant of residential and commercial CO_2 emissions, and these patterns are colinear with latitude and continentality. The geographic and environmental influences on industrial CO_2 emissions are less pronounced than for the residential and commercial sectors and this is likely due to underlying drivers associated with labor intensiveness and proximity to raw materials. CO_2 emissions from electricity production show patterns confirming the presence of large coal-fired production facilities in the Midwest and low-population locations in the Intermountain and southwest regions. Per capita transportation CO_2 emissions show patterns consistent with dependence upon average trip distance with higher values in the low-population Mountain and intermountain West.

[50] 4. The spatial gradients of residential, commercial and electricity production CO_2 emissions versus CDD and HDD can be used as a rough proxy for the relationship between increased temperature due to climate change and CO_2 emissions. The analysis finds that the emissions associated with per capita increases in electricity production are roughly five times the reduction in per capita residential and commercial emissions due to lessened heating requirements. Taking into account carbon intensity of fuel sources associated with these sectors suggests that the energy requirement of increased cooling will still be over twice that of the energy saved through lessened heating needs.

[51] 5. Spatial clustering analysis clearly shows the presence of strong statistically significant nonrandom clusters of fossil fuel CO_2 emissions and these spatial patterns are distinct for each economic sector. The spatial size or domain of the spatial clusters is also dependent upon economic sector and absolute versus per capita metrics. Per capita emissions in residential and transportation sector show the largest spatial clustering of high per capita values though significant, large clusters exist for the commercial and industrial sectors as well.

[52] These conclusions imply a number of things for carbon cycle science. It is clear that population is an unreliable and biased proxy for the spatial distribution of fossil fuel CO_2 emissions, particularly when the scale of analysis goes below the state spatial scale. Atmospheric CO_2 measurement campaigns aimed at supplying additional measurement constraints to carbon budget efforts require accurate, spatially resolved emission source estimates [*Mays et al.*, 2009]. This is particularly true of studies that have begun to examine regional and urban-scale spatial domains (North American Carbon Program, Mid-continent intensive interim synthesis, 2008, available at http://nacp.ornl.gov/mast-dc/int_synth_mci.shtml). In order to best utilize atmospheric measurements the emission source and intervening atmospheric transport must be determined with accurate space/time representation. Large point sources, such as electricity production or industrial facilities are of particular note in this regard. Most importantly, the heterogeneity of the fossil fuel CO_2 emissions strongly suggests that regional or urban carbon cycle studies will have a unique suite of source characteristics and the sectoral composition and magnitude will be important considerations in the design of atmospheric measurement campaigns. Our recent research on quantification of building/street-level emissions in the city of Indianapolis demonstrates the significant source heterogeneity in urban environments [*Zhou and Gurney*, 2010]. Finally, the spatial distribution of point (e.g., electricity production) versus area-based sources (e.g., residential and commercial) is an important factor in the coupling to atmospheric transport modeling. For example, point source characteristics such as the precise location, stack height and exit velocity become critical factors for transport and atmospheric sampling as the spatial domain reaches the urban scale.

[53] The conclusions also have implications for emissions mitigation policy. National and subnational (state aggregates or individual state) policy design can consider strategies that most efficiently target spatially coherent opportunities. For example, efforts aimed at individual consumers versus urban or regional aggregates might focus on different portions of the U.S. and that may depend upon the sector chosen and analysis of per capita versus absolute emission metrics. The residential versus electricity production sectors demonstrate this vividly; normalization by population has a dramatic spatial influence on the residential sector but little impact on electricity production.

[54] The spatial domain of the emissions clustering also raises important policy considerations. It suggests that strategies that encompass multistate regions, such as the clusters of high residential per capita emissions in New England and Midwest, may provide more efficient policy gains in particular sectors, than those at the individual state level (and certainly at the national level). This recognition intersects critically with regional development goals, already encumbered by overlapping metropolitan, county, and state governance constraints.

[55] Finally, the relationship between external temperature and sectoral emissions suggests that the increased electricity consumption due to space cooling requirements under a warmer climate may outweigh the savings generated by lessened space heating. This holds implications for energy systems planning and future fuel mix needs.

[56] The results presented here offer a number of future research avenues. Understanding the underlying mechanistic (social, economic, technological) emission drivers is a

logical complement to the spatial analysis presented here and will further assist mitigation policy strategies. Further downscaling to the building/street level offers additional means to evaluate the estimation methods by availing of data sets such as utility billing, traffic monitoring, and manufacturing statistics. It also offers mitigation opportunities at the municipal scale, where mitigation goals established at the national level will be operationalized by city planners and local sustainability programs. For example, recent research attempted comprehensive quantification of fossil fuel CO_2 emissions at the scales of individual buildings in urban environments [*Zhou and Gurney*, 2010]. The relationship between HDD/CDD and sectoral emissions must be further explored with multiyear emissions and temperature data to better quantify the relationship suggested here through spatial gradients and is a crucial component of energy systems planning in a warmer world.

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