Urban Form, Air Pollution, and CO₂ Emissions in Large U.S. Metropolitan Areas

Bradley Bereitschaft a & Keith Debbage b

a University of Nebraska at Omaha
b University of North Carolina at Greensboro

Published online: 20 Jun 2013.

To cite this article: Bradley Bereitschaft & Keith Debbage (2013) Urban Form, Air Pollution, and CO₂ Emissions in Large U.S. Metropolitan Areas, The Professional Geographer, 65:4, 612-635, DOI: 10.1080/00330124.2013.799991

To link to this article: http://dx.doi.org/10.1080/00330124.2013.799991

PLEASE SCROLL DOWN FOR ARTICLE

Taylor & Francis makes every effort to ensure the accuracy of all the information (the “Content”) contained in the publications on our platform. However, Taylor & Francis, our agents, and our licensors make no representations or warranties whatsoever as to the accuracy, completeness, or suitability for any purpose of the Content. Any opinions and views expressed in this publication are the opinions and views of the authors, and are not the views of or endorsed by Taylor & Francis. The accuracy of the Content should not be relied upon and should be independently verified with primary sources of information. Taylor and Francis shall not be liable for any losses, actions, claims, proceedings, demands, costs, expenses, damages, and other liabilities whatsoever or howsoever caused arising directly or indirectly in connection with, in relation to or arising out of the use of the Content.

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan,
Urban Form, Air Pollution, and CO₂ Emissions in Large U.S. Metropolitan Areas

Bradley Bereitschaft
University of Nebraska at Omaha

Keith Debbage
University of North Carolina at Greensboro

In this article we explore the relationships between urban form and air pollution among 86 U.S. metropolitan areas. Urban form was quantified using preexisting sprawl indexes and spatial metrics applied to remotely sensed land cover data. Air pollution data included the nonpoint source emission of the ozone (O₃) precursors nitrogen oxides (NOx) and volatile organic compounds (VOCs), the concentration of O₃, the concentration and nonpoint source emission of fine particulate matter (PM2.5), and the emission of carbon dioxide (CO₂) from on-road sources. Metropolitan areas that exhibited higher levels of urban sprawl, or sprawl-like urban morphologies, generally exhibited higher concentrations and emissions of air pollution and CO₂ when controlling for population, land area, and climate.

Key Words: air pollution, air quality, urban form, urban morphology, urban sprawl.

Cities account for less than 3 percent of the Earth’s land surface, yet they produce 78 percent of anthropogenic carbon emissions and substantial quantities of airborne toxins and pollutants (O’Meara 1999; United Nations 2006). These emissions adversely affect air quality at local and regional scales and are believed to play a significant role in global climate change (Grimm et al. 2008). Although many factors affect air quality, such as climate, topography, and economics, the way in which cities grow and evolve spatially is a crucial component (Lu and Turco 1995; Newton 1997; Ewing, Pendall, and Chen 2003; Stone 2008; Clark, Millet, and Marshall 2011). Urban form, the spatial organization and arrangement...
of people, buildings, and infrastructure, dramatically affects how cities function, how efficiently they utilize resources, and the quantity of pollution they produce (Environmental Protection Agency [EPA] 2001; Ewing, Pendall, and Chen 2003; Borrego et al. 2006). In this article we explore the relationships among urban form, air pollution concentrations and emissions, and the emission of carbon dioxide (CO₂) among large U.S. metropolitan areas.

The mechanisms by which urban form might influence air quality, air pollutant emissions, and the release of CO₂ are well documented (Newman and Kenworthy 1989; Frank and Pivo 1994; Lariviére and Lafrance 1999; Ewing, Pendall, and Chen 2003; Handy, Cao, and Mokhtarian 2005; Borrego et al. 2006). Note that the term air quality refers to the ambient concentration of air pollution as measured using air quality monitors, whereas air pollution could refer to both the anthropogenic emission of air pollutants and their ambient concentrations. Among the most studied connections between urban form and air pollution are the effects of urban form on travel behavior, vehicle kilometers traveled (VKT), and tailpipe emissions (Frank, Stone, and Bachman, et al. 2000; Ewing, Pendall, and Chen 2003; Frank et al. 2006; Grazi, Van der Bergh, and Van Ommeren 2008). As urban areas become less dense and urban land use becomes more segregated, residents use single-occupant vehicles more often and tend to drive further to reach work and other destinations (Frank and Pivo 1994; Ewing, Pendall, and Chen 2003; Vance and Hedel 2007; Bartholomew and Ewing 2009). As residents rely less on walking, biking, or transit, the per capita emission of tailpipe pollutants such as CO₂, nitrogen oxides (NOₓ), particulate matter (PM), and carbon monoxide (CO) increase. Urban form can also affect air quality by influencing local meteorology, including the urban heat island (UHI) effect, and the energy efficiency of buildings (Taha and Bornstein 1999; Weng 2003; Ewing and Rong 2008).

The production and emission of air pollutants (including CO₂) affect human health at local, regional, and global scales. Tropospheric ozone (O₃) and fine particulate matter (PM2.5) are known to contribute to life-threatening cardiovascular and pulmonary illness (Laden et al. 2006; Jacobson 2008; Jerrett et al. 2009). The World Health Organization (2006) estimated that exposure to outdoor air pollution was responsible for nearly 1.2 million premature deaths in 2004. The anthropogenic emission of CO₂, a greenhouse gas (GHG), is thought to be a major contributor to the rise in global temperature, which has the potential to adversely affect millions worldwide through sea level rise and climate change (Khasnis and Nettleman 2005; Cline 2007; Dasgupta et al. 2007). A rise in atmospheric CO₂ might also exacerbate the effects of air pollution. A modest 1°C increase in global temperature could result in an additional 1,000 air pollution–related deaths annually in the United States and 21,600 additional deaths worldwide (Jacobson 2008).

A variety of models have been developed to estimate the impact of alternative patterns of urban growth on air pollution and GHG emissions (Borrego et al. 2006; Civerolo et al. 2007; De Ridder et al. 2008; Kahyaoglu-Koracin et al. 2009; Hankey and Marshall 2010; Hixson et al. 2010). In general, these models have indicated that an increase in high-density, compact development is associated with a reduction in the emission of GHG and the air pollutants nitrogen dioxide (NO₂), O₃ precursors, and PM. Hankey and Marshall (2010) estimated that comprehensive compact urban development could reduce GHG cumulative emissions in the United States by as much as 15 to 20 percent between 2000 and 2020. Compact development, however, might also increase exposure to air pollution by locating more people in dense urban areas where certain air pollutants, such as PM, are typically found in the highest concentration (Marshall et al. 2005; De Ridder et al. 2008; Hixson et al. 2010).

A limited number of studies have empirically evaluated the direct associations between urban form and the emission or concentration of air pollution (Ewing, Pendall, and Chen 2003; Stone 2008; Schweitzer and Zhou 2010; Bechle, Millet, and Marshall 2011; Clark, Millet, and Marshall 2011; see Table 1). Using the Smart Growth America (SGA) composite urban sprawl index (Ewing, Pendall, and Chen 2002), Ewing, Pendall, and Chen (2003) and Stone (2008) observed that large U.S. cities with higher levels of urban sprawl, or more sprawl-like urban morphologies (i.e., lower densities, less street connectivity), experienced significantly higher O₃ precursor emissions, higher O₃ concentrations (annual fourth highest daily maximum eight-hour average), and
<table>
<thead>
<tr>
<th>Study</th>
<th>n scale</th>
<th>Pollutant variables</th>
<th>Urban form variables</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ewing, Pendall, and Chen (2003)</td>
<td>83 U.S. PMSAs</td>
<td>O₃ concentration</td>
<td>Residential density, centrality, mix of uses, street connectivity</td>
<td>Higher residential density significantly associated with lower O₃ concentration. Controls: metropolitan population, household size, % population of working age, and per capita income.</td>
</tr>
<tr>
<td>Stone (2008)</td>
<td>45 U.S. MSAs (urban form); PMSAs (air quality)</td>
<td>O₃ exceedances, VOC + NOx emissions</td>
<td>SGA sprawl index, residential density, centrality, mix of uses, street connectivity</td>
<td>Residential density negatively associated with combined NOx/VOC emissions, mean number of O₃ exceedances. Street connectivity also negatively associated with O₃ exceedances. Overall sprawl index positively associated with O₃ exceedances. Controls: temperature, precipitation, and metropolitan population.</td>
</tr>
<tr>
<td>Schweitzer and Zhou (2010)</td>
<td>80 U.S. “regions” (associated with SGA index PMSAs)</td>
<td>O₃ concentration, PM2.5 concentration, exposures</td>
<td>SGA sprawl index</td>
<td>Increase in urban sprawl (SGA Index) associated with significant decrease in O₃ concentrations but significant increase in O₃ exposures and PM2.5 exposures. Controls: close proximity to major streets, industries (y/n)</td>
</tr>
<tr>
<td>Bechle, Millet, and Marshall (2011)</td>
<td>83 global cities ~MSA scale</td>
<td>NO₂ concentration</td>
<td>Compactness and contiguity of development</td>
<td>Contiguity of urban development negatively associated with NO₂ concentrations, no significant association between compactness and NO₂. Controls: income, population.</td>
</tr>
<tr>
<td>Clark, Millet, and Marshall (2011)</td>
<td>111 U.S. urban areas</td>
<td>O₃ exposures, PM2.5 exposures, LAQI</td>
<td>City shape, jobs–housing imbalance, population centrality, population density, road density, transit supply</td>
<td>Population density significantly associated with higher PM2.5 exposures, population centrality significantly associated with lower O₃ and PM2.5 exposures, and transit supply negatively associated with PM2.5 exposures. Controls: O₃ season temp., dilution rate, income, land area, region.</td>
</tr>
</tbody>
</table>

Note: PMSA = primary metropolitan statistical area; VOCs = volatile organic compounds; NOx = nitrogen oxides; SGA = Smart Growth America; MSA = metropolitan statistical area; LAQI = long-term air quality index.
significantly more $O_3$ exceedances (number of days per year $O_3 > 0.075$ ppm). Using satellite-derived measurements of urban form, Bechle, Millet, and Marshall (2011) found that among eighty-three global cities, those that exhibited less contiguous built-up areas experienced, on average, higher concentrations of NO$_2$. Schweitzer and Zhou (2010) took a finer scale approach and found that neighborhoods in less sprawling U.S. metropolitan areas, as evaluated using the SGA sprawl index (Ewing, Pendall, and Chen 2002), generally exhibited lower concentrations of $O_3$ but higher $O_3$ and PM2.5 exposures due to a greater concentration of people living in areas with higher air pollutant concentrations. Finally, Clark, Millet, and Marshall (2011) analyzed 111 U.S. Census-defined urban areas and found that those with more centralized populations were associated with lower population-weighted PM2.5 and $O_3$ concentrations, whereas those with higher population densities were associated with significantly higher population-weighted PM2.5 concentrations.

In this article we address three unanswered research questions regarding the empirical relationships between urban form/urban sprawl and the emission and concentration of air pollution. First, do the significant associations between measures of urban form/urban sprawl and the nonpoint source emission of $O_3$ precursors, the concentration of $O_3$, and the concentration and nonpoint source emission of PM2.5 previously observed at the less extensive urban area (Clark, Millet, and Marshall 2011) and primary metropolitan statistical area (PMSA; Ewing, Pendall, and Chen 2003; Stone 2008; Schweitzer and Zhou 2010) scales also exist at the scale of large metropolitan statistical areas (MSAs) and combined statistical areas (CSAs)? Given that the dispersal of air pollution is not confined by municipal, urbanized area, or even metropolitan boundaries, it is possible that a higher degree of association between urban form and air quality will be observed at this broader scale. Furthermore, by controlling for confounding variables omitted in previous studies (e.g., regional population, metropolitan land area), we aim to more accurately assess the strength of the associations between urban form and the concentration and emission of air pollution. Second, are metropolitan areas with higher levels of urban sprawl, or sprawl-like urban forms, associated with higher CO$_2$ emissions from on-road (i.e., mobile) sources? Although the emission and ambient concentration of many air pollutants have decreased in recent decades, the emission of CO$_2$ from automobiles and other anthropogenic sources has continued to rise (Raupach et al. 2007; Smith 2009). We hypothesize that urban areas with more sprawl-like urban morphologies will have higher CO$_2$ emissions from on-road sources, presumably due to enhanced automotive dependency and the associated rise in VKT. The third and final research question we address is whether the SGA composite urban sprawl index developed by Ewing, Pendall, and Chen (2002), which incorporates four measures of urban form (residential density, land use mix, degree of centering, and street accessibility), is a better predictor of air pollutant emissions (including CO$_2$) and concentrations than urban sprawl indexes or other metrics based on a single measure of urban form. If so, this would provide evidence suggesting that urban sprawl, and its associated effects, can be most accurately evaluated by quantifying several different dimensions of urban form.

**Methods**

A series of linear regression models was used to assess the degree of association between the emission and concentration of air pollutants and the emission of CO$_2$ (dependent variables), and various measures of urban form and urban sprawl (independent variables). Air pollution data were collected for eighty-six metropolitan areas located throughout the conterminous United States with populations greater than 500,000 as of the 2000 census (Figure 1). This cohort of “large” metropolitan areas included twenty-three MSAs and sixty-three CSAs. An MSA contains “at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties” (Office of Management and Budget 2010, 2). CSAs are generally larger than MSAs both in population and in area and include any combination of
The study area included twenty-three metropolitan statistical areas (MSAs) and sixty-three combined statistical areas (CSAs).

multiple adjacent metropolitan and micropolitical statistical areas with an employment interchange of at least 15 percent.

**Air Pollution**

Dependent variables included (1) the estimated nonpoint source emissions of the O3 precursors NOx and volatile organic compounds (VOCs) and PM2.5 from nonpoint sources in 2000, (2) the estimated emissions of CO2 from “on-road” (i.e., automotive) sources in 2002, and (3) the ambient concentrations of O3 (fourth maximum eight-hour) and PM2.5 (twenty-four-hour average) averaged over the five-year period 1998 to 2002. Annual concentrations were averaged over multiple years to reduce the impact of annual fluctuations. We chose to use nonpoint source emissions in our analysis to exclude emissions by large point-source industrial facilities, which are not expected to be affected significantly by urban form. On average, nonpoint source emissions accounted for 73 percent of total NOx emissions, 91 percent of VOC emissions, and 81 percent of PM2.5 emissions. On-road emissions accounted for about 33 percent of total CO2 emissions.

Air pollution data were obtained from the U.S. EPA’s AirData database; CO2 emissions data were available through Arizona State University’s Vulcan Project (Gurney et al. 2002). Nonpoint emissions of O3 precursors and PM2.5 were averaged for all counties within each metropolitan area. O3 and PM2.5 concentrations were averaged for all air quality monitors in continuous operation between 1998 and 2002 within each metropolitan area boundary. There were 981 monitors in total, of which 594 recorded O3 concentrations and 596 recorded PM2.5 concentrations. The mean number of monitors for each metropolitan area was seven for O3 and 13 for PM2.5.

**Urban Sprawl Indexes**

Among the many measures of urban sprawl available in the literature, five urban sprawl indexes were chosen for use in this study because (1) they were modeled on U.S. metropolitan areas and (2) they were applied to a large subset of cities (more than eighty-three), providing a sample size large enough for statistical analysis (see Table 2). The urban sprawl indexes by El-Nasser and Overberg (2001), Lopez and Hynes (2003), and Sutton (2003) are based on population density, although they each use unique methodologies and data sets. The index developed by El-Nasser and Overberg...
Table 2  Descriptive statistics for urban sprawl indexes and four Smart Growth America sprawl index components

<table>
<thead>
<tr>
<th>Index/Component</th>
<th>Number of metros(^a)</th>
<th>Brief description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smart Growth America Index (Ewing, Pendall, and Chen 2002)</td>
<td>64</td>
<td>Composite index derived from four measures of urban form via principal component analysis</td>
</tr>
<tr>
<td>Street accessibility</td>
<td>64</td>
<td>Average block size, no. blocks &lt; 500 ft.(^2)</td>
</tr>
<tr>
<td>Degree of centering</td>
<td>64</td>
<td>Density gradient, no. population centers, proximity of population to central business district</td>
</tr>
<tr>
<td>Land use mix</td>
<td>64</td>
<td>Jobs-population ratio, land use diversity, residential-nonresidential proximity</td>
</tr>
<tr>
<td>Residential density</td>
<td>64</td>
<td>Gross pop. density, prop. of pop. living at high densities</td>
</tr>
<tr>
<td>Sutton (2003) Index (high)(^b)</td>
<td>76</td>
<td>Regression of population vs. area; cities above “sprawl line” less sprawling</td>
</tr>
<tr>
<td>Sutton (2003) Index (low)(^b)</td>
<td>84</td>
<td>Regression of population vs. area; cities above “sprawl line” less sprawling</td>
</tr>
<tr>
<td>Lopez and Hynes (2003) Index</td>
<td>85</td>
<td>% of metropolitan population (2000) in high- vs. low-density census tracts</td>
</tr>
<tr>
<td>USA Today Index(^c)</td>
<td>86</td>
<td>% of metropolitan population (1990 and 1999) in census-defined urban areas</td>
</tr>
</tbody>
</table>

\(^a\)Indicates the number of metropolitan areas, out of the original sample of eighty-six metropolitan areas, with > 500,000 residents in 2000, for which scores exist for each sprawl index.

\(^b\)High represents high urban threshold; low represents low urban threshold.

\(^c\)By El-Nasser and Overberg (2001).

(2001; published in USA Today) ranked 271 metropolitan areas according to the percentage of the metropolitan population residing in census-defined urban areas in 1990 and 1999. The overall sprawl score was obtained by adding the ranking from both years. Lopez and Hynes (2003) calculated a sprawl index score using the percentage of metropolitan area population (2000) in high-density census tracts versus low-density census tracts.

Rather than using census-defined urban area boundaries or census tracts, Sutton (2003) systematically defined the extent of urban areas using nighttime satellite imagery. The radiance levels of urban areas at night were used to create two urban boundaries: a high threshold based on higher radiance levels and containing more compact urban core areas and a low threshold based on lower radiance levels and containing more extended conurbations. Two regressions, one for each threshold, described the relationships between the natural log of residential population and the natural log of urban area (km\(^2\)) for 300 urban clusters. When the data were displayed using scatterplots, the regression line (termed the sprawl line) represented the average relationship between population and areal extent for urban clusters in the United States. Cities above the sprawl line had higher than expected populations and lower levels of sprawl, while those below the line had lower than expected populations and higher levels of sprawl.

The SGA sprawl index developed by Ewing, Pendall, and Chen (2002) is a composite index based on four components of urban form: residential density, land use mix, street accessibility, and degree of centering. Each component was similarly derived from multiple variables using principal components analysis (PCA). To allow comparison between metropolitan areas, Ewing, Pendall, and Chen rescaled each of the four components to have a mean of 100 and standard deviation of 25. In addition to Ewing, Pendall, and Chen’s (2002) overall sprawl score, we use the four components of urban form as independent variables, similar to Stone (2008).

Urban Continuity and Shape Complexity

Nine landscape metrics (Table 3) were used to calculate two composite measures of urban form not captured by the urban sprawl indexes: the continuity and shape complexity of urban development. Each of the landscape metrics employed in this study has been used previously to quantify urban form, describe the temporal evolution of urban land patterns, or model future urban growth (Luck and Wu 2002; Herold, Goldstein, and Clarke 2003; Wei et al. 2006;
<table>
<thead>
<tr>
<th>Landscape metric</th>
<th>Equation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area weighted mean patch fractal dimension (AWMPFD)</td>
<td>$FD = \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \frac{2n_{ij}}{p_{ij}} \right) \left( \alpha_{ij} \right)$</td>
<td>Where $m$ is the number of patch types, $n$ is the number of patches of a class, $p_{ij}$ is the perimeter (m) of patch $ij$ (urban), $\alpha_{ij}$ is the area (m) of patch $ij$, and $A$ is the total landscape area (m$^2$)</td>
</tr>
<tr>
<td>Area weighted mean shape index (AWMSI)</td>
<td>$AWMSI = \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \frac{p_{ij}}{m_{ij}e_{ij}} \right) \left( \alpha_{ij} \right)$</td>
<td>Where $m$ is the number of patch types, $n$ is the number of patches of a class, $p_{ij}$ is the perimeter of patch $ij$ (urban) measured in number of cell surfaces, $m_{ij}$ is the minimum perimeter possible for patch $ij$, and $A$ is the total landscape area (m$^2$)</td>
</tr>
<tr>
<td>Clumpiness index (CLUMPY)</td>
<td>Given $G_i = \left( \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}} + min e_i \right)$</td>
<td>CLUMPY = $\begin{cases} \left( g_{ii} - \frac{1}{2} \right) / \left( \frac{1}{2} + min e_i \right) &amp; \text{if } G_i &lt; P_i &lt; 0.5 \ \left( g_{ii} - \frac{1}{2} \right) / \left( \frac{1}{2} + min e_i \right) &amp; \text{otherwise} \end{cases}$ Where $g_{ii}$ is the number of like adjacencies between pixels of class $i$, $g_{ik}$ is the number of adjacencies between pixels of class $i$ and class $k$, $min e_i$ is the minimum perimeter of a patch type $i$ for a maximally aggregated patch type, and $P_i$ is the proportion of the landscape occupied by patch type $i$</td>
</tr>
<tr>
<td>Contagion (CONTAG)</td>
<td>$CONTAG = \left[ \sum_{i=1}^{m} \sum_{k=1}^{m} \left( \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right] \left[ \sum_{i=1}^{m} \sum_{k=1}^{m} \left( \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right) \right]$</td>
<td>Where $P_i$ is the proportion of the landscape occupied by class $i$, $g_{ik}$ is the number of adjacencies between pixels of classes $i$ and $k$, and $m$ is the number of patch types</td>
</tr>
<tr>
<td>Contiguity (CONTIG)</td>
<td>$CONTIG = \left[ \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ijr} \right] \left( \frac{a_{ij}}{v} \right)$</td>
<td>Where $c_{ijr}$ is the contiguity value for pixel $r$ in patch $ij$, $v$ is the sum of the values in a 3x3 moving window, and $a_{ij}$ is the area of patch $ij$ in terms of number of cells</td>
</tr>
<tr>
<td>Edge density (ED)</td>
<td>$ED = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} e_{ij}}{A} \times 10,000$</td>
<td>Where $e_{ij}$ is the total edge length (m) of class $i$ in the landscape, and $A$ is the total landscape area. The result is multiplied by 10,000 to convert to hectares</td>
</tr>
<tr>
<td>Largest patch index (LPI)</td>
<td>$LPI = \frac{\max(a_{ij})}{A}$</td>
<td>Where $\max(a_{ij})$ is the area (m$^2$) of the largest urban patch and $A$ is the total landscape area (m$^2$). The result is multiplied by 100 to convert to a percentage</td>
</tr>
<tr>
<td>Landscape shape index (LSI)</td>
<td>$LSI = \frac{e_i}{min e_i}$</td>
<td>Where $e_i$ is the total length of edge of class $i$ (number of cell surfaces), including all landscape boundary and background edge segments involving patch type $i$, and $min e_i$ is the minimum total length of edge of class $i$</td>
</tr>
<tr>
<td>Percentage of like adjacencies (PLADJ)</td>
<td>$PLADJ = \frac{g_{ii}}{\sum_{k=1}^{m} g_{ik}} \times 100$</td>
<td>Where $g_{ii}$ is the number of like adjacencies between pixels of class $i$ and $g_{ik}$ is the number of adjacencies between pixels of class $i$ and class $k$</td>
</tr>
</tbody>
</table>

Note: Adapted from McGarigal et al. (2002).
Urban continuity is a measure of the degree of aggregation or fragmentation among patches of urban development. Urban continuity can be interpreted as a measure of “leapfrog” development. Bechle, Millet, and Marshall (2011) employed a similar measure in their study and found that more contiguous urban areas experienced, on average, significantly lower concentrations of NO₂. Shape complexity is based on a perimeter-to-area ratio and can be interpreted as the “jaggedness” of the urban boundary as well as the porosity (i.e., the intermixing of urban and nonurban land cover) of the urban landscape. Huang, Lu, and Sellers (2007) used landscape metrics to quantify urban complexity and porosity, among other spatial attributes, to compare regional differences in urban form among seventy-seven metropolitan areas. Urban continuity and shape complexity are used in this analysis to expand our understanding of the potential connections between specific attributes of urban form and air pollution. In contrast to previously used measures of urban form, urban continuity and shape complexity represent spatial information derived from multiple satellite-based metrics. Using PCA-derived factors, rather than a set of landscape metrics, reduces redundancy and aids in the modeling process by limiting the number of independent variables.

To compute the landscape metrics, land cover data were obtained from the Multi-Resolution Land Characteristics Consortium’s (MRLC) National Landcover Dataset (NLCD). The 2001 NLCD (Homer et al. 2007) has a 30-meter spatial resolution and is comprised of sixteen land cover types classified using the Anderson Level II classification scheme (Anderson et al. 1978; Figure 2A). The original sixteen land cover types were reclassified into two classes: urban and nonurban (Figure 2B). The urban class included four land uses designated as “developed” under the Anderson Level II classification code. The nonurban class included all other land cover, such as forest, cropland, grassland, and water. The reclassified land cover data were extracted using the county-level boundaries of each metropolitan area.

In the NLCD, which defines urban land cover using percent impervious surface area, substantial quantities of “urban” land cover exist within rural areas, including rural roads, highways, and farmhouses. Therefore, to obtain a more accurate assessment of urban form, it was necessary to identify “pockets” of urbanization within each metropolitan area and exclude urban land cover located in rural areas. The U.S. Department of Defense Meteorological Satellite Program’s Operational Linescan System captures the intensity of anthropogenic lighting, providing a quantitative and systematic means of delineating the urbanized boundary within each metropolitan area. Light intensity values ranged from 0 to 63, with 0 representing no lighting and 63 representing very bright lights typical of dense urban centers. By overlaying the light intensity and urban land cover data sets it was possible to approximate an urban boundary by visual inspection. Areas with a light intensity value less than 13 were considered rural; those with a light intensity value of 13 or greater were considered urbanized (Figure 2C). A similar procedure was performed by Sutton et al. (2010) to classify rural, peri-urban, and urban areas in Australia. Although Sutton et al. (2010) classified areas with a light intensity value of 11 or higher as urban, they noted that “this threshold for Australia is much lower than what it would be for the United States” (122). In some metropolitan areas, such as New York, these “pockets” of urbanization covered nearly the entire land area, whereas in others, such as Las Vegas, they constituted a small proportion of the total area. Rural areas within each metropolitan area boundary (i.e., the land not contained with the pockets of urbanization) were discarded, leaving behind only the urban land cover contained within the pockets of urbanization (Figure 2D).

PCA was used to extract two urban form components from the nine landscape metrics: urban continuity and urban shape complexity. The landscape metrics that loaded high under continuity included contagion, contiguity index, percentage of like adjacencies, largest patch index, and the clumpiness index; those that loaded high under shape complexity included area-weighted mean shape index, landscape shape index, area-weighted mean patch fractal dimension, and edge density. Together, urban continuity and shape complexity explained 79.7 percent of the total variance among the nine original measures of urban form. Among the sample of eighty-six
metropolitan areas, the two components are represented as standard deviations. Urban continuity ranged from a low of –2.6 SD in Greenville–Spartanburg, South Carolina, to a high of 2.0 SD in Salt Lake City, Utah. Shape complexity ranged from –2.4 SD in Lafayette, Louisiana, to 2.0 SD in Atlanta, Georgia. Examples of metropolitan areas along these two continuums are shown in Figure 3.

**Control Variables**

The emission and concentration of air pollution are influenced by a number of variables not directly related to urban form. Although the list of potential influences is extensive, six control variables were selected for having strong theoretical or empirically informed ties to air pollution (Elminir 2005; Camalier, Cox,
Figure 3  Examples of metropolitan areas with urban continuity and shape complexity that range from approximately –2 to 2 standard deviations from the mean. Continuity represents the aggregation of urban land cover and can be interpreted as a measure of “leapfrog” development. Shape complexity is a measure of the “jaggedness” of the urban boundary. The metropolitan areas are displayed at a 1:1,300,000 scale.
and Dolwick 2007; Jacob and Winner 2009; Lai and Cheng 2009). These variables include metropolitan population, regional population (within 500 km), metropolitan land area (km²), average annual wind speed, and two climate variables: temperature and moisture. The climate variables were derived from an original set of seven climatic and meteorological variables (i.e., average annual temperature, average maximum temperature, average precipitation, number of cloudy days, cooling degree days, heating degree days, relative humidity) using PCA. In the PCA, average annual wind speed was not well represented by either the temperature or moisture component and was therefore retained as a separate control variable. Precipitation, cloud cover, and wind speed vary under the influence of cyclonic and anticyclonic weather systems and can therefore provide some measure of synoptic-scale weather patterns (Camalier, Cox, and Dolwick 2007; Lai and Cheng 2009). As an alternative to wind direction, which has a variable impact on air quality (Blumenthal, White, and Smith 1978; Lioy and Samson 1979), regional population (i.e., the number of people living within 500 km of each metropolitan area) was included in the concentration models to control for the intermetropolitan dispersal of air pollution. The climatic and meteorological data were obtained from the National Oceanic and Atmospheric Administration’s National Climatic Data Center, and averaged over a period of more than thirty years (i.e., climate normals). Population data were obtained from the U.S. Census Bureau. Additional explanatory variables used in previous studies (Ewing, Pendall, and Chen 2003; Clark, Millet, and Marshall 2011), such as income, household size, and percentage of population of working age, were not significant predictors of air pollution and therefore were not included in the analysis.

**Linear Regression Models**

A total of sixty linear regression models were performed to evaluate the associations among six dependent and seventeen independent variables. The five control variables, temperature, moisture, wind speed, metropolitan population, and regional population, were included in all models in which the dependent variable was ambient concentrations. The four control variables, temperature, moisture, metropolitan population, and metropolitan land area (km²), were included in all models in which the dependent variable was nonpoint source emissions. Each regression model therefore included as independent variables one or more measures of urban form/urban sprawl combined with four or five relevant control variables. The use of control variables was necessary to account for potential variations in air pollutant concentrations and emissions not attributable to urban form and thereby provide a more accurate assessment of the statistical associations between urban form and air pollution.

With significant correlations between urban sprawl indexes, each index was run in a separate regression model to reduce multicollinearity. Similar to Stone (2008), the four measures of urban form that make up the SGA index were also run in separate models to reduce multicollinearity and avoid overspecifying the models by having fewer than ten observations per parameter. The two uncorrelated components of urban form, urban continuity and urban shape complexity, were included in the same set of regression models to assess the associations between the spatial geometry of urban development and air pollution among all eighty-six metropolitan areas in the sample.

The goal of the regression analysis was to evaluate the degree of association between measures of urban form/urban sprawl and the ambient concentration and/or nonpoint source emission of O₃, VOCs, NOₓ, PM2.5, and CO₂ while controlling for multiple confounding factors.

**Results and Discussion**

All regression models were statistically significant at the $p < 0.001$ level and had moderate to high predictive power with model-adjusted $r^2$ values ranging from 0.360 to 0.961. Multicollinearity among all regression models was low, with variance inflation factors (VIF) less than 3 and condition indexes (CI) less than 25. The regression models identified several significant associations between urban form/urban sprawl and the ambient concentration and emission of air pollutants, suggesting that associations between urban form and air pollution are discernible at the MSA/CSA scale (Table 4). Organized by urban form/urban sprawl
variables, we describe here only those associations between urban form and air pollution statistically significant at the 95 percent confidence level.

The urban form components continuity and shape complexity were significantly associated with air pollutant emissions. One standard deviation increase in urban continuity resulted in an 8,647 ton (9 percent) reduction in annual VOC emissions (Table 4; Figure 4). For every one standard deviation increase in urban shape complexity, annual NOx emissions increased by 8,083 tons (8.7 percent) and annual PM2.5 emissions increased by 3,055 tons (12.4 percent). Using a measure of urban form similar to urban continuity, Bechle, Millet, and Marshall (2011) observed a significant (24 percent) reduction in the concentration of NO2 with each standard deviation increase in the contiguity of urban development. Although we did not observe a significant association between our measure of urban continuity and the ambient concentration of either O3 or PM2.5, the nonpoint source (largely automotive-based) emissions of VOCs, NOx, PM2.5, and CO2 generally increased as the land cover within large metropolitan areas exhibited less continuous, more complex spatial patterns (Table 4).

Urban continuity represents the degree to which the urban landscape is fragmented; higher urban continuity is expected among urban areas that are less fragmented, with more contiguous and less “leapfrog” development. Less open space between urban developments should result in shorter automotive trips and fewer emissions from nonpoint (primarily mobile) sources. Urban shape complexity provides a composite measure of urban area-to-perimeter ratio or the “jaggedness” of the urban boundary. Less compact urban landscapes with highly convoluted, irregular boundaries common among suburban and exurban areas are also expected to increase the number and duration of automotive trips.

### Table 4  Linear regression model results: B coefficients for urban form/urban sprawl variables

<table>
<thead>
<tr>
<th>Urban form/sprawl variablea</th>
<th>VOCs</th>
<th>NOx</th>
<th>PM2.5</th>
<th>CO2</th>
<th>N⁴</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban continuity</td>
<td>−0.760</td>
<td>0.161</td>
<td>−8,647**</td>
<td>−1,684</td>
<td>−770</td>
</tr>
<tr>
<td>Urban shape complexity</td>
<td>0.793</td>
<td>0.134</td>
<td>6,829³</td>
<td>8,083**</td>
<td>3,055**</td>
</tr>
<tr>
<td>Residential density</td>
<td>−0.275***</td>
<td>−0.085**</td>
<td>−244</td>
<td>−802**</td>
<td>−94.5</td>
</tr>
<tr>
<td>Land use mix</td>
<td>0.015</td>
<td>−0.005</td>
<td>−86.8</td>
<td>139</td>
<td>38.8</td>
</tr>
<tr>
<td>Degree of centering</td>
<td>−0.086</td>
<td>−0.029⁹</td>
<td>67.2</td>
<td>−413**</td>
<td>−55.8</td>
</tr>
<tr>
<td>Street accessibility</td>
<td>−0.103**</td>
<td>−0.033**</td>
<td>−333</td>
<td>−86.8</td>
<td>−77.9</td>
</tr>
<tr>
<td>SGA Sprawl Index⁵</td>
<td>−0.113**</td>
<td>−0.042**</td>
<td>−195</td>
<td>−261*</td>
<td>−65.1</td>
</tr>
<tr>
<td>Sutton Sprawl Index (high)</td>
<td>−0.068**</td>
<td>−0.020*</td>
<td>−129</td>
<td>−11.3</td>
<td>−86.7*</td>
</tr>
<tr>
<td>Sutton Sprawl Index (low)⁶</td>
<td>−0.076**</td>
<td>−0.012</td>
<td>−164</td>
<td>−79.7</td>
<td>−106**</td>
</tr>
<tr>
<td>Lopez &amp; Hynes Index</td>
<td>0.090*</td>
<td>0.018</td>
<td>119</td>
<td>−145</td>
<td>−24.1</td>
</tr>
<tr>
<td>USA Today Sprawl Index</td>
<td>0.016*</td>
<td>0.005*</td>
<td>12.8</td>
<td>−10.9</td>
<td>−3.75</td>
</tr>
</tbody>
</table>

Note: VOCs = volatile organic compounds; NOx = nitrogen oxides; SGA = Smart Growth America.

²Urban continuity and urban shape complexity were run within the same linear regression model; all other urban form/urban sprawl variables were run within separate regression models. Each model with O3 or PM2.5 concentrations as the dependent variable (columns 3 and 2) contained four control variables in addition to the urban form/urban sprawl variable(s): metropolitan population, regional population (within 500 km), and the climate-meteorological variables temperature, moisture, and wind speed. Each model with VOC, NOx, PM2.5, or CO2 emissions as the dependent variable (columns 3–6) contained four control variables in addition to the urban form/urban sprawl variable(s): metropolitan population, metropolitan land area (km²), and the climate variables temperature and moisture.

³Ozone (O3) and fine particulate matter (PM2.5) concentrations were averaged over a five-year period (1998–2002). O3 concentrations are reported as parts per billion (ppb); PM2.5 concentrations are reported as micrograms per cubic meter (μg/m³).

⁴Total estimated nonpoint source emissions for each metropolitan area for the year 2000.

⁵Number of data points (metropolitan areas) per set of models.

⁶The SGA and Sutton sprawl indexes are inverse scales (i.e., a negative B coefficient indicates an increase in air pollution with increasing urban sprawl).

*p < 0.1.

**p < 0.05.

***p < 0.01.
The results therefore support the theoretical linkages between urban form and nonpoint (primarily automotive) emissions.

Given the significant associations between urban continuity, urban shape complexity, and nonpoint source emissions, it was unexpected that significant associations were not also observed between the two urban form components and ambient concentrations (Table 4). Stone (2008) has suggested that, in addition to affecting emissions, urban form might influence the formation of ground-level ozone through non-emissions-based mechanisms such as the enhancement of the UHI effect and by affecting the distribution of air quality monitors, which might be more geographically dispersed in less centralized metropolitan areas. A more dispersed monitoring network could result in higher average O₃ concentrations, which tend to be highest outside dense urban cores, such as those found in New York or Chicago (Figure 5), while having the opposite effect on average PM2.5 concentrations, which are often highest in and around the central city (Figure 6). In dense urban cores, high concentrations of nitrogen oxide (NO) react with O₃ to form nitrogen dioxide and molecular oxygen (Jenkin and Clemitshaw 2000). Non-emissions-based mechanisms such as these might also help explain why several significant associations were observed between the urban sprawl indexes/SGA sprawl index components and ambient concentrations, despite few associations between these variables and nonpoint source emissions. It is important to note, however, that unlike Stone (2008), we used estimates of emissions from nonpoint sources only, rather than total emissions. Although the majority of PM2.5 and O₃ precursor emissions originated from nonpoint sources, any air pollution contributed by large point sources would have introduced some error in our air quality models. Additional research will be needed to identify and assess the potential non-emissions-based mechanisms by which urban form could affect air quality.

In contrast to urban continuity and shape complexity, the individual urban sprawl indexes were most strongly associated with ambient concentrations. With the exception of the
Figure 5  Average annual fourth maximum eight-hour ozone (O₃) concentrations (ppb) between 1998 and 2002 in (A) Atlanta, Georgia, (B) New York, New York, (C) Chicago, Illinois, (D) Los Angeles, California, (E) Houston, Texas, and (F) Seattle, Washington, and Portland, Oregon. The highest O₃ concentrations in large U.S. metropolitan areas were generally found in suburban areas beyond the urban core, although some low-density cities, such as Atlanta (A), experienced relatively high concentrations throughout the urban region. Areas with average annual eight-hour O₃ concentrations above 0.75 ppb are classified by the U.S. Environmental Protection Agency as in “nonattainment.” O₃ surfaces were estimated from ground-level air monitors (dots) using ordinary kriging. (Color figure available online.)
Figure 6  Average annual twenty-four-hour fine particulate matter (PM2.5) concentrations (μg/m³) between 1998 and 2002 in (A) Atlanta, Georgia, (B) New York, New York, (C) Chicago, Illinois, (D) Los Angeles, California, (E) Houston, Texas, and (F) Seattle, Washington, and Portland, Oregon. In contrast to ozone, the highest PM2.5 concentrations in large U.S. metropolitan areas were generally found in or near the central city. Areas with average annual twenty-four-hour PM2.5 concentrations above 35 μg/m³ are classified by the U.S. Environmental Protection Agency as in “nonattainment.” PM2.5 surfaces were estimated from ground-level air monitors (dots) using ordinary kriging. (Color figure available online.)

regional population control variable, the urban sprawl indexes were often the best predictors of air pollutant concentrations (Table 4). The SGA sprawl index developed by Ewing, Pendall, and Chen (2002) was significantly associated with both O₃ and PM2.5 concentrations. Both the SGA sprawl index and the Sutton (2003) index are inverse scales; therefore, the
negative B coefficients for the two indexes in Table 4 indicate that metropolitan areas with lower levels of sprawl on average exhibit lower concentrations of $O_3$ and PM2.5. According to the SGA sprawl index, a single standard deviation increase in urban sprawl (i.e., a decrease of twenty-five units) was associated with a 2.8 ppb (3.4 percent) rise in $O_3$ concentrations, and a 1.0 $\mu$g/m$^3$ (7.8 percent) increase in PM$_{2.5}$ concentrations (Figure 7). Three of the four sprawl indexes based on a single measure of urban form (population density), including Sutton (2003; high threshold), Sutton (2003; low threshold), and El-Nasser and Overberg (2001), also indicated a significant ($p < 0.05$) positive relationship between increasing levels of sprawl and $O_3$ concentrations (Table 4). Ranked among the ten most sprawling large (500,000+) metropolitan areas in the United States by Ewing, Pendall, and Chen (2002) and Sutton (2003), metro Atlanta (Figures 5A, 6A) and the Riverside–San Bernardino area of western Los Angeles (i.e., the “Inland Empire”; Figures 5D, 6D) exhibited some of the highest average annual concentrations of $O_3$ and PM2.5 over the five-year study period.

Overall, there is little evidence that the SGA index, based on four different measures of urban form, is a better predictor of air pollution than sprawl indexes based solely on population density. Although the SGA index was the only urban sprawl index significantly associated with PM2.5 concentrations, the Sutton index (low threshold) was the only urban sprawl index significantly associated with PM2.5 emissions. In contrast to the indexes developed by El-Nasser and Overberg (2001) and Lopez and Hynes (2003), the Sutton Index is a scale-adjusted measure of population density that evaluates the per capita land use consumption of each metropolitan area relative to all other metropolitan areas in the sample. The other two indexes evaluate the population density of each metropolitan area independently. Sutton (2003) also used nighttime satellite imagery, rather than census-based thresholds,
to delineate the urban boundary within each metropolitan area. This methodology might have resulted in a more accurate overview of metropolitan density, thereby resulting in the only sprawl index significantly associated with both the concentration of \( \text{O}_3 \) and the nonpoint source emission of PM2.5. Furthermore, with the Sutton Index significantly associated with PM2.5 emissions only when calculated using a low urban threshold, the extent of the urban boundary appears to be an influential variable. The low urban threshold included a more extensive portion of the urban periphery, providing a more inclusive measure of per capita land use consumption throughout the metropolitan area.

An increase in residential density and street network connectivity (two of the four SGA sprawl index components) was associated with a significant decrease in the ambient concentration of \( \text{O}_3 \) and PM2.5 (Table 4). One standard deviation increase in residential density was associated with a 6.9 ppb (8 percent) decrease in the average concentration of \( \text{O}_3 \) and a 2.1 \( \mu \text{g/m}^3 \) (16 percent) decrease in the ambient concentration of PM2.5. A single standard deviation increase in street network connectivity was associated with a more modest 2.6 ppb (3 percent) reduction in \( \text{O}_3 \) concentrations and a 0.825 \( \mu \text{g/m}^3 \) (6.2 percent) reduction in PM2.5 concentrations (Table 4; Figure 4). Ewing, Pendall, and Chen (2003) and Stone (2008) also observed that metropolitan areas with higher residential densities and more connected street networks tend to have lower ambient \( \text{O}_3 \) concentrations and fewer annual \( \text{O}_3 \) exceedances. Here we have demonstrated that residential density and street network connectivity might also significantly affect the ambient concentration of other harmful airborne pollutants, such as PM2.5.

An increase in residential density and degree of centering (i.e., the proximity of housing and jobs to the central business district) was also significantly associated with a decrease in the nonpoint source emission of NOx, an \( \text{O}_3 \) precursor (Table 4). In contrast to NOx, an increase in VOC emissions was significantly associated with a decrease in urban continuity only. Whereas VOCs represent a diverse group of compounds emitted by a wide variety of sources (e.g., automobiles, solvents, oil and gas production), the majority of NOx are from "mobile," primarily automotive, sources (EPA 2011). The significant associations observed between NOx emissions and multiple measures of urban form are likely indicative of the impact of urban form on travel behavior and automotive emissions. Stone (2008) found a significant negative association between \( \text{O}_3 \) precursor emissions and residential density only; however, he modeled VOCs and NOx together and used total emissions rather than nonpoint source emissions.

Residential density was the only urban form variable significantly associated with \( \text{CO}_2 \) emissions from on-road sources at the \( p < 0.05 \) level (Table 4). For every standard deviation increase in residential density, the average large metropolitan area could expect to emit approximately 1.9 million fewer tons of \( \text{CO}_2 \) from on-road vehicles. For the Atlanta CSA, this would constitute a 22 percent reduction in \( \text{CO}_2 \) emissions from on-road sources. With better access to transit, fewer automobiles per capita, and less distance between destinations facilitating walking and biking, denser urban areas are considerably “greener” in terms of \( \text{CO}_2 \) emissions per capita than any tree-lined suburb.

Among the control variables, regional population was the most consistently significant predictor of \( \text{O}_3 \) and PM2.5 concentrations. For each standard deviation increase in regional population (i.e., for each additional 19.6 million people living within 500 km), \( \text{O}_3 \) concentrations increased by an average of 5.72 ppb (6.6 percent), and PM2.5 increased by an average of 1.0 \( \mu \text{g/m}^3 \) (7.5 percent; Figure 8). The existence of an urban agglomeration the size of the New York CSA within a 500-km radius would therefore be expected to raise a metropolitan area’s \( \text{O}_3 \) concentrations by approximately the same amount as would reducing residential density by one standard deviation. In addition to having moderate to low levels of urban sprawl (El-Nasser and Overberg 2001; Ewing, Pendall, and Chen 2002; Lopez and Hynes 2003; Sutton 2003), the air quality of the two major urban centers of the Northwestern United States, Portland, Oregon, and Seattle, Washington, likely benefited from a relatively low regional population, minimizing interregional transport of air pollution from outside urban and industrial centers (Figures 5F, 6F).

More populous metropolitan areas also generally exhibited higher concentrations and nonpoint source emissions. For every one standard
deviation increase in population, approximately 3.14 million people, PM2.5 concentrations increased by an average of 1.39 \( \mu g/m^3 \) (10.5 percent). Only one model, which contained residential density as the urban form/urban sprawl variable, indicated a significant positive association between metropolitan population and O_3 concentrations. The relatively weak relationship between metropolitan population and metropolitan-scale O_3 concentrations reflects the fact the largest metropolitan areas (e.g., New York, Chicago; Figure 6) typically contain the densest and most extensive urban cores, which generally exhibit relatively low concentrations of O_3. When residential density was controlled for (i.e., included in the regression model), one standard deviation increase in metropolitan population was associated with a 5.27 ppb (6.1 percent) rise in O_3 concentrations. An increase in metropolitan population was also significantly associated with an increase in air pollutant emissions, with one standard deviation increase in population associated with, on average, a 5.1 million ton (146 percent) increase in CO_2 emissions from on-road sources, a 92,964 ton (97 percent) increase in VOC emissions, a 90,330 ton (97 percent) increase in NOx emissions, and a 13,855 ton (56 percent) increase in PM2.5 emissions from nonpoint sources (Figure 9). Larger metropolitan areas in terms of land area were also associated with an increase in NOx, PM2.5, and CO_2 emissions, although the average percentage increase was much less than with each standard deviation increase in metropolitan population (Figure 9).

The climate factor of temperature was significantly associated with O_3 concentrations only: A single standard deviation increase in “temperature” was associated with an average
Figure 9  Average percentage change in air pollutant nonpoint source emissions (from on-road sources only for CO₂) for every one standard deviation increase in each of five control variables. Not all control variables were significant predictors of air pollutant emissions in every model; therefore, only when control variables were significant at the \( p < 0.10 \) level were they included in these averages. Note that although the control variables metropolitan population and land area were significantly correlated \( (r = 0.561, p < 0.01) \), the collinearity of the variables was low \( (VIF < 5) \). (Color figure available online.)

2.04 ppb (2.4 percent) rise in O₃ concentrations (Figure 8). Higher temperatures and an increase in sunlight promote the chemical reactions that produce ground-level O₃ (Seinfeld and Pandis 1998). High temperatures are also associated with stable, often “stagnant” atmospheric conditions and could further contribute to high ozone concentrations by increasing the biogenic emission of isoprene (Chung 1977; Sharkey et al. 1996; Biesenthal et al. 1997). The climate factor of moisture, which represents both precipitation and humidity, was positively associated with PM2.5 concentrations, as well as the nonpoint source emissions of PM2.5, VOCs, and NOx. One standard deviation increase in moisture was associated with an average 0.722 µg/m³ (5.4 percent) increase in PM2.5 concentrations (Figure 8) and considerably higher percentage increases in nonpoint source emissions (Figure 9). Due to precipitation scavenging and wet deposition, an increase in precipitation is expected to remove airborne pollutants and reduce ambient concentrations (Naresh, Sundar, and Shukla 2007). Particulate matter, however, might increase with a rise in humidity (Dawson, Adams, and Pandis 2007). Furthermore, both precipitation and PM2.5 concentrations are generally higher in the eastern United States relative to the western half of the country and therefore the significant positive association between the two variables could in part be an artifact of this regional variation. The final control variable, wind speed, was negatively associated with both O₃ and PM2.5 concentrations (Figure 8). One standard deviation increase in wind speed (2.4 km/hr) was associated with an average 1.61 ppb (1.87 percent)
decrease in O$_3$ concentrations and an average 1.12 μg/m$^3$ (8.5 percent) decrease in PM2.5 concentrations. Higher wind speeds have the effect of more rapidly dispersing and diluting airborne pollutants, reducing concentrations and exposures in urban areas (Dawson, Adams, and Pandis 2007; Jacob and Winner 2009).

An increase in residential density might improve air quality and contribute to a reduction in per capita CO$_2$ emissions at the metropolitan scale primarily by decreasing automotive dependency and tailpipe emissions (Frank, Stone, and Bachman 2000; Ewing, Pendall, and Chen 2003; Grazi, Van der Bergh, and Van Ommeren 2008). Although an increase in residential density would likely benefit the majority of metropolitan residents, the results of Clark, Millet, and Marshall (2011) and Schweitzer and Zhou (2010) suggest that increasing residential density could raise the population-weighted air pollutant concentrations (i.e., air pollutant exposures) for some urban residents. Schweitzer and Zhou (2010) found that O$_3$ and PM2.5 exposures were generally higher in more compact metropolitan areas, despite significantly lower O$_3$ concentrations overall. Furthermore, neighborhoods with a higher proportion of minority and poor residents experienced higher concentrations of, and exposures to, both O$_3$ and PM2.5. An increase in population density might reduce automotive dependency, but it also concentrates people in urban neighborhoods with poorer overall air quality than that of surrounding suburban and exurban areas (Schweitzer and Zhou 2010). Planning for density therefore becomes an issue of environmental justice, particularly at the metropolitan level. Simulations suggest that by relocating to peripheral suburban areas, residents might reduce their exposure to certain air pollutants, including VOCs, particulate matter, and nitrogen dioxide, simultaneously contributing to a decline in regional air quality by increasing the total volume of automotive traffic (Hewitt 1991; Baldasano, Delgado, and Calbo 1998; De Ridder et al. 2008).

Technological innovations, such as the introduction of the electric car, will likely offset the higher exposures associated with dense living conditions. A significant reduction in tailpipe emissions, for example, would reduce the amount of pollutants circulating between high-rise buildings and decrease the amount of pollution inhaled by pedestrians. If the energy used to power electric or hydrogen-based vehicles is generated by burning fossil fuels outside the city, there would likely be only a moderate reduction in the gross emission of air pollution and CO$_2$ (Colella, Jacobson, and Golden 2005; Samaras and Meisterling 2008). The implications for human health, however, could be significant if emissions shift away from population centers, thereby reducing the exposure of urban residents to high concentrations of air pollution. In this scenario, an increase in density might reduce the emission and concentration of air pollutants and CO$_2$ without raising exposures.

**Limitations of the Study**

Any attempt to statistically evaluate the strength of association between urban form and air pollution will be complicated by a range of confounding factors. Although we included a number of control variables in our models, there exist additional factors that might be of relevance, including topography and regional variations in air pollution. Topographical barriers, such as mountain ranges, can have a negative impact on local air quality by limiting the horizontal dispersal of air pollutants (Chang-Han and Pielke 1986; Lu and Turco 1995). Mountain ranges, however, might also have a positive effect on air quality in some windward locations by increasing precipitation and in leeward areas by geographically blocking air pollution from upwind sources (Ganev et al. 2003; Lin et al. 2005). Even within a single metropolitan area there could be significant localized variations in air quality due to topography and other obstructions (Lu and Turco 1995; Ulke and Andrade 2001). Our use of relatively broad-scale MSAs and CSAs, with air quality monitors distributed over thousands of square kilometers, served to average out localized impacts on air quality. Additionally, because most of the eighty-six metropolitan areas in the study contained few or no significant (i.e., mountainous) topographical features, topography likely had a minimal impact on our results.

In addition to the interurban transport of air pollution, there typically exist broad regional variations in air quality. For example, between 1998 and 2002, cities east of the Mississippi River exhibited significantly higher...
average concentrations of both particulate matter and ground-level ozone compared with cities west of the Mississippi. Although we attempted to control for sources of air pollution outside each metropolitan area using a regional population (within 500 km) variable, some error might still have been introduced by regional variations in air pollution due to differences in economic activity, industrial output, and the spatial arrangement of urban and industrial centers (e.g., the degree to which cities are downwind of one another). Future analyses could use dispersion and spatial autoregressive models to more fully assess and control for the impact of external sources of air pollution.

Although the majority of anthropogenic emissions of PM2.5 and O3 precursors are from nonpoint sources, emissions from both point and nonpoint sources, as well as emissions from nonanthropogenic sources, can impact the concentration of air pollution. Therefore, it is probable that the strength of the statistical associations observed between urban form and ambient air quality were affected by some degree by sources of air pollution, such as large industrial facilities, the emissions of which are not influenced by urban form. Finally, our analysis of urban form and air pollution was confined to the United States and based on data collected on or around the year 2000. Data collected during a different time period, or outside the United States, might yield different results.

Conclusion

Our analysis of urban form, air pollution, and CO2 emissions yielded three primary insights. First, certain measures of urban form and urban sprawl are robust predictors of O3 and, to a lesser extent, PM2.5. Although the SGA index was calculated primarily from a set of PMSAs, and the air pollution data were calculated at the broader MSA/CSA scale, higher levels of urban sprawl were still significantly associated with higher concentrations of both O3 and PM2.5. Second, residential density was a significant predictor of O3 and PM2.5 concentrations, the nonpoint source emission of NOx, and the on-road emission of CO2. Therefore, any planning strategy aimed at reducing air pollution and CO2 emissions at the metropolitan level should include affordable higher density alternatives to low-density residential sprawl. Third, the satellite-derived measures of urban form, urban continuity and shape complexity, were significantly associated with O3 precursor and PM2.5 emissions and in the hypothesized directions: metropolitan areas with urban land cover geometries characteristic of low-density, discontinuous urban sprawl (i.e., lower urban continuity and higher shape complexity) generally experienced higher emissions from nonpoint sources. Given these relationships, it might prove fruitful to further investigate the links that exist between the geometry of large urban areas and energy use, air pollution, and carbon emissions to better understand how the built environment affects the natural environment at local to global scales. With the majority of population growth over the next thirty years expected to occur within the nation’s largest metropolitan areas, how urban form affects urban function and efficiency will become increasingly essential to the nation’s long-term sustainability.

Literature Cited


BRADLEY BEREITSCHAFT is an Assistant Professor in the Department of Geography/Geology at the University of Nebraska at Omaha, 6001 Dodge Street, Omaha, NE 68182. E-mail: bbereitschaft@unomaha.edu. His research interests include sustainable development, community planning, urban–environment interactions, urban climate, and the impacts of urban sprawl on human and natural systems.

KEITH DEBBAE is a Professor in the Department of Geography at the University of North Carolina at Greensboro, 1009 Spring Garden Street, Greensboro, NC 27403. E-mail: kgdebbe@uncg.edu. His research interests include urban development, tourism, and air transportation.