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Research Paper

# Urban form and air quality in the United States

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## HIGHLIGHTS

- The relationship between urban spatial structure and air quality is explored.
- Fragmentary urban form is associated with low air quality.
- Larger areas of forests in a county are associated with higher PM2.5 exceedance days.
- Proximate forests to urban areas reduce the number of AQI exceedance days.

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## ABSTRACT

In this paper, we investigate the relationship between urban spatial structure and air quality in the United States. By using urban landscape metrics framework, we empirically examine whether fragmentary and sprawling urban patterns are associated with low air quality. We develop an algorithm to correct for biases within the urban landscape metrics in the United States. Controlling for demographic variables and economic activity, we find a strong relationship between the type and pattern of development and pollutant levels. The finding is not biased by the presence of relatively rural counties in the dataset suggesting that paying close attention to the urban form might have some implications for air quality.



## 1. Introduction

The configuration of urban development has long been known to be a major cause of poor air quality (Stone, Mednick, Holloway, & Spak, 2007). Previous research has demonstrated the relationship between sprawl indicators such as density, street network, and leap-frog development, and air quality (Cervero & Kockelman, 1997; Frank & Pivo, 1994). However, the exact relationship between development patterns and air quality has been elusive due to difficulties in quantifying patterns or using indicators poorly suited for spatial analysis (Borrego et al., 2006). By using remote sensing land cover data we are better able to tease out the impacts of specific development characteristics such as fragmentation and leap-frog development. Patterns of configuration represented through urban landscape metrics offer alternatives to typical characterizations that use population distribution while simultaneously overcoming some of their spatial limitations (Burchfield, Overman, Puga, & Turner, 2006; Kaza, 2013). Furthermore, the relationship between urban settlement patterns and air quality is understudied in relatively underdeveloped areas. In this paper, we study the relationship between air quality and urban form in a more comprehensive manner than before in the United States. We find that poor air quality and urban fragmentation are related in all types of counties and not just in metropolitan regions. Using land cover data we are also able to explore the mitigating potential of forest land cover that are proximate to urban areas.

Land cover data is an attractive way of measuring urban patterns because it overcomes the fundamental limitations inherent to measures that rely solely on demographic data. Most research on this topic has been limited in terms of coverage and spatial continuity. Most sprawl indices and urban form metrics are calculated at the Metropolitan Statistical Area (MSA) level missing both rural areas outside MSAs and finer grain patterns within them. Comprehensive characterizations take into account facets such as population density, continuity, concentration (Galster et al., 2001) or land use mix and street accessibility (Ewing, Pendall, & Chen, 2003). These characterizations are geographically limited to specific regions due to data availability and computational considerations.

Unlike demographic data, land cover indicators provide comprehensive data of both urban and rural areas for the conterminous United States. As land cover data is derived from satellite imagery, continuous monitoring is possible. Landscape metrics characterize urban development independent of demographic changes as well

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as providing information about non-urban uses. Accordingly, we can then test the composition as well as configuration of urban patterns in both urban and non-urban land cover information. We take advantage of this to explore the potential importance of mixing of multiple types of land uses.

Forests in close proximity to urban development are a potentially important factor in determining air quality. Forests contribute to air quality conditions by both mitigating and producing Ozone precursor emissions. Trees are estimated to remove 0.7 million metric tons of pollutants per year in the United States (Nowak, Crane, & Stevens, 2006). Precursor compounds (VOC & NOX), which form Ozone are also produced by biogenic sources. As tree cover and urban area are simultaneously captured in satellite data and fragmentary urban form could be associated with interspersed forest cover, the degree to which the two are mixed may be relevant to air quality.

Landscape metrics often used to study habitat fragmentation can also be used to characterize urban form. Unlike traditional landscape metrics that use natural areas as their main focus, urban landscape metrics depend on identifying patches of contiguous urban areas. Once these patches are identified, various metrics such as number, mean patch area, etc. can be readily calculated. Urban landscape metrics have been used to monitor patterns of growth at a metropolitan level but their use has been limited to select geographies (Bereitschaft & Debbage, 2013; Buyantuyev, Wu, & Gries, 2010; Seto & Fragkias, 2005) or was marred by data quality issues (Kaza, 2013). In this paper, we correct some of the issues associated with using raw land cover data within the United States while testing two prevailing hypotheses: (1) more fragmented and expansive patterns of development are correlated with bad air quality than more contiguous configurations, and (2) the relative mixing of urban and forest land impacts air quality.

## 2. Background

Fragmentary and dispersed patterns of urban development, without high quality transit are associated with high automobile use, longer trip lengths and subsequent air quality problems. This connection forms the basis for most emissions modeling (Borrego et al., 2006). However, urban patterns also affect air quality. Impervious surface cover are associated with Ozone ($O_3$) formation (Taha, 2008), building configurations with pollutant dispersal (Sini, Anquetin, & Mestayer, 1996) and leapfrog development with increased $NO_2$ (Bechle, Millet, & Marshall, 2011).

For example, Hartford County, CT and Fulton County, GA are comparable in terms of population, metropolitan population, density, and urban area. They are likewise comparable according to the sprawl index criteria of Ewing et al. (2003). Fulton, however, generates significantly more air pollutants and suffers a greater number of days with excessive Ozone levels annually. We hypothesize, as previous modeling studies have (Martins, 2012), that the difference in air quality outcomes can be explained, in part, by the differences in urban development patterns.

The few existing empirical studies that examined the relationship between urban patterns and air quality focused primarily on metropolitan regions. In their study of over 100 metropolitan areas, Clark, Millet, and Marshall (2011) found that characteristics such as population centrality explain as much variation in pollutant concentration as climate. In a similar study on $O_3$ exceedances, sprawling regions are associated with higher mean annual exceedances after controlling for precursor emissions (Stone et al., 2007). However, the urban form characteristics used in these studies are limited to measures based on demographic (Bento, Cropper, Mobarak, & Vinha, 2005; Downs, 1999; Lopez, 2014) or employment data (Glaeser, Kahn, & Chu, 2001) within the metropolitan regions. Bereitschaft and Debbage (2013), an exception, use urban landscape metrics to characterize the relationship between emissions and urban form based on landscape metrics, however, use modeled emissions as the dependent variable rather than air quality.

There are many advantages to using land cover data to calculate the metrics of urban form. First, a comprehensive database that covers both urban and rural areas for the conterminous United States is readily available. Continuous monitoring is possible and the data are updated on a continuous five-year cycle through satellite imagery. Second, we can account for the intermixing of different land cover types without focusing solely on urbanized area. Tree cover is an important mitigating factor for many types of emissions (Escobedo & Nowak, 2009; Zipperer, Sisinni, Pouyat, & Foresman, 1997). Tree cover and urban area are simultaneously captured in satellite data; it is possible to explore how fragmentary urban form could be associated with interspersed forest cover and have impacts on air quality. Third, many areas in the US are losing population, especially in the rust belt and rural counties, while the total developed area in the county remains the same or is increasing. This is due to disconnect between urbanized land and population dynamics. Urbanization is largely irreversible while people and jobs are mobile; metrics that are characterized only by demographic and economic variables at any given time are less likely to capture the phase difference between urban land conversion and economic and demographic changes in a place. While there are some disadvantages that we will discuss later, we find using satellite data to describe urban patterns is useful and complementary to standard accounts.

To demonstrate the differences in the urban form indicators of various studies, we compared the performance of various MSAs. Only a few metropolitan areas are persistently present in the top ten sprawled areas according to various indices (see Table 1), the most prominent being Atlanta and Miami MSA. While the indicators were calculated using different datasets and at different time points, this shows how land cover data and demographic data are complementary to describe the urban spatial structure. Even within a single metropolitan area there are significant differences. For example, within the New York MSA gross county level population density ranges from 166 to 27,470 (per sq. km) suggesting significant variation within the urban form. Similarly, the number of days with bad air quality ranges from 4 to 19 within the counties in the New York MSA. Thus, while Table 1 refers to MSAs, the rest of this study focuses on counties.

We begin by describing the various data sources and data processing steps to arrive at a county level sample. We then briefly describe the state of air quality and urban morphological indicators in the US in the last decade. The results of the empirical analysis are discussed with some caveats and we conclude with further questions this research raises.

## 3. Data description & methods

Our cross-sectional analysis uses data circa 2006, compiled from a number of sources for the conterminous United States. We restrict our attention to the Criteria Air Pollutants (CAP) as defined by the Clean Air Act. In particular, we study $O_3$ and particulate matter (PM2.5) in greater detail due to their acute health impacts. We use the number of days Air Quality Index (AQI) exceeds 100 as a measure of air quality in a county.

To compute the Gini coefficient of population density (at a block group level), we used population data from 2000 Census available in Almquist (2010). This coefficient measures centrality and ranges from 0 (uniform density) to 1 (highly concentrated density). We use county character (Rural, Mixed Rural, Mixed Urban and Urban) as

**Table 1**
Most sprawled MSA according to various indices.

| Indices based primarily on demographic characteristics | | |
|---|---|---|
| Ewing et al. index (2000) | Low density (2006) | Lopez index (2010) |
| Hickory-Lenoir-Morganton, NC | Duluth, MN-WI | Anderson,SC |
| Atlanta-Sandy Springs, GA | Fargo, ND-MN | Anniston-Oxford, AL |
| Clarksville, TN-KY | Topeka, KS | Burlington, NC |
| Prescott, AZ | Longview, TX | Columbus, IN |
| Nashville, TN | Yakima, WA | Dalton, GA |
| Baton Rouge, LA | Lake Havasu City-Kingman, AZ | Danville, VA |
| Riverside-San Bernardino-Ontario, CA | Sioux Falls, SD | Decatur, AL |
| Greenville-Mauldin-Easley, SC | Fort Smith, AR-OK | Dothan, AL |
| Augusta-Richmond County, GA-SC | Beaumont-Port Arthur, TX | Elizabethtown, KY |
| Kingsport-Bristol-Bristol, TN-VA | Champaign-Urbana, IL | Evansville, IN-KY |
| Indices based primarily on land cover data | | |
| Most fragmented (2006) | Largest standard deviation in urban areas (2006) | Burchfield et al. index (1992) |
| Atlanta-Sandy Springs, GA | Chicago-Naperville, IL | Miami-Fort Lauderdale, FL |
| Kansas City, MO-KS | Detroit-Dearborn-Livonia, MI | Billings, MT |
| Riverside-San Bernardino-Ontario, CA | Fort Lauderdale, FL | Abilene, TX |
| Washington-Arlington, DC-VA-MD-WV | Los Angeles-Long Beach-Glendale, CA | Laredo, TX |
| St. Louis, MO-IL | Anaheim-Santa Ana-Irvine, CA | Memphis, TN-AR-MS |
| Pittsburgh, PA | Houston-Sugar Land-Baytown, TX MSA | Phoenix-Mesa, AZ |
| Houston-Sugar Land-Baytown, TX | Nassau County-Suffolk County, NY | Dallas-Fort Worth, TX |
| Dallas-Plano-Irving, TX Metro Division | West Palm Beach-Boca Raton, FL | Denver-Boulder-Greeley, CO |
| New York-Jersey City, NY–NJ | Miami, FL | Oklahoma City, OK |
| Fort Worth-Arlington, TX | Cleveland-Elyria-Mentor, OH | New York–New Jersey, NY–NJ |

Data vintage years are in parentheses.

defined by Isserman (2005) to further understand different relationships at varying stages of urban development. We acquired inter-decennial demographic data from the American Community Survey (US Census Bureau, 2012), economic data from the Bureau of Economic Analysis (US Department of Commerce, 2010), air quality data from the US Environmental Protection Agency (2013) and the remote sensing data from United States Geological Survey (Fry et al., 2011). Weather data such as precipitation and mean summer temperature is from the National Climatic Data Center.

### 3.1. Air quality data

The United States Environmental Protection Agency (EPA) continuously collects air quality data from approximately 1300 monitoring stations across the United States stations measuring PM2.5 and $O_3$. We obtained daily AQI data for these two pollutants from the EPA because they are considered important from a public health perspective (Bell, McDermott, Zeger, Samet, & Dominici, 2004; Krewski et al., 2009). The AQI value is based on National Ambient Air Quality Standards (NAAQS) and runs from 0 to 500, with the value 100 deemed the acceptable standard from a public health perspective.

In the case of multiple monitoring stations within a county we used the maximum daily AQI value. We then counted the number of days where AQI > 100 as exceedance days in that year; high number of exceedance days are associated with lower air quality for that county. To account for exceptional events (e.g. forest fires) that might affect the concentration levels, we averaged the days between 2004 and 2008 using 'plyr' (Wickham, 2011). This summarization reduces the data from a 3.3 to 1.5 million records to about 700 records (see Fig. 1). While Ozone is an issue in many metropolitan areas it is not limited to urban counties; the distribution of PM2.5 exceedance days also has a long right tail in rural and mixed rural counties. However, on average, urban and mixed urban counties suffer from worse air quality compared to rural counties, evidenced by the inter quartile range of the exceedance days.

To measure the overall air quality, we acquired the annual number of days in different AQI categories at a county level published by the EPA at http://www.epa.gov/airdata/ad_rep_aqi.html. These categories are Good (AQI 0–50), Moderate (51–100), Unhealthy for Sensitive groups (101–150), Unhealthy (151–200), Very Unhealthy (201–300) and Hazardous (>300). The overall daily AQI is determined by the most substantial pollutant of each day; the EPA is required by the Clean Air Act to track the six CAP pollutants: CO, $NO_2$, $O_3$, $SO_2$, PM2.5, PM10. We considered all days that are not in the Good and Moderate AQI categories. As with the other air quality data sets, the average between 2004 and 2008 is considered. While urban counties tend to have higher number of days with low air quality, the mixed rural counties have a long right tail of the distribution (Fig. 1).

### 3.2. Urban landscape metrics

The land cover data, circa 2006, was produced by the US Geological Survey and retrieved from the Multi-Resolution Land Characteristics Consortium website (Fry et al., 2011). Each of the 30 m pixels (~9 billion for the conterminous US) was classified into 16 national land cover data (NLCD) level II land cover classes. For each county in the conterminous US, we extracted urban land cover classes (NLCD 21–24) and forest classes (NLCD 41–43). We then derived urban form metrics based not only on the amount of urban land but the relative location of urban and forest classes within each county. These metrics included number of urban patches, mean patch area, standard deviation of area, eccentricity of the standard ellipse and the ratio of forest land within 1 km of the urban patches to total urban land (see Fig. 2).

Urban patch is defined as contiguous area that is classified as urban land cover. However, urban landscape metrics pose a special problem due to identification of transport networks as urban land. As these transport networks connect distinct urban fragments, metrics such as mean patch area, number of patches and the Standard Deviation Ellipse (SDE) are skewed, especially in the rural counties. For example, the towns surrounding Lexington, KY are connected by the highway system and appear as a single connected patch (see Fig. 3a), therefore the unadjusted metrics would underestimate urban fragmentation in this area.

To rectify this issue, the following data processing algorithm was applied to each county in the conterminous US. Using a road

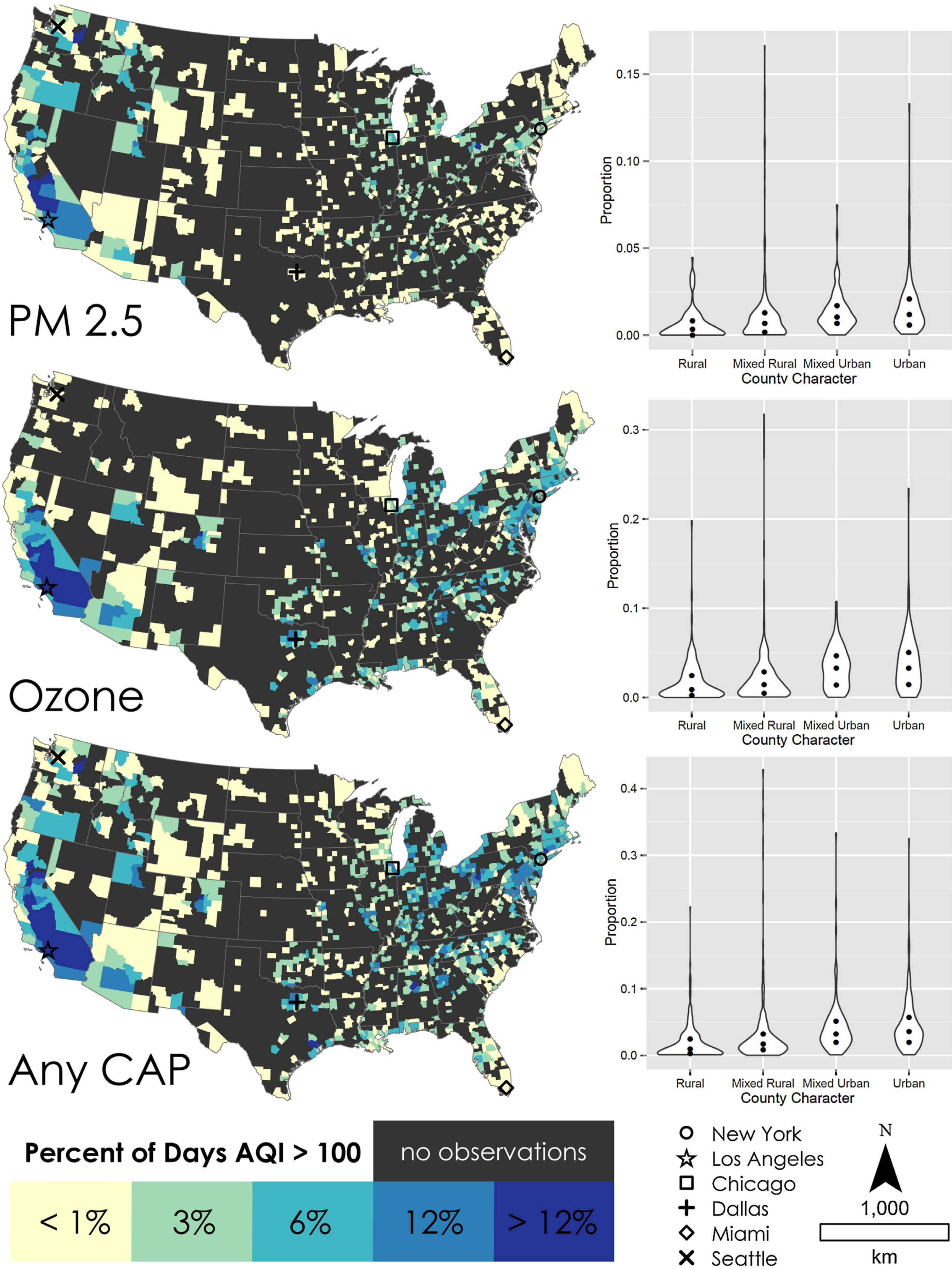
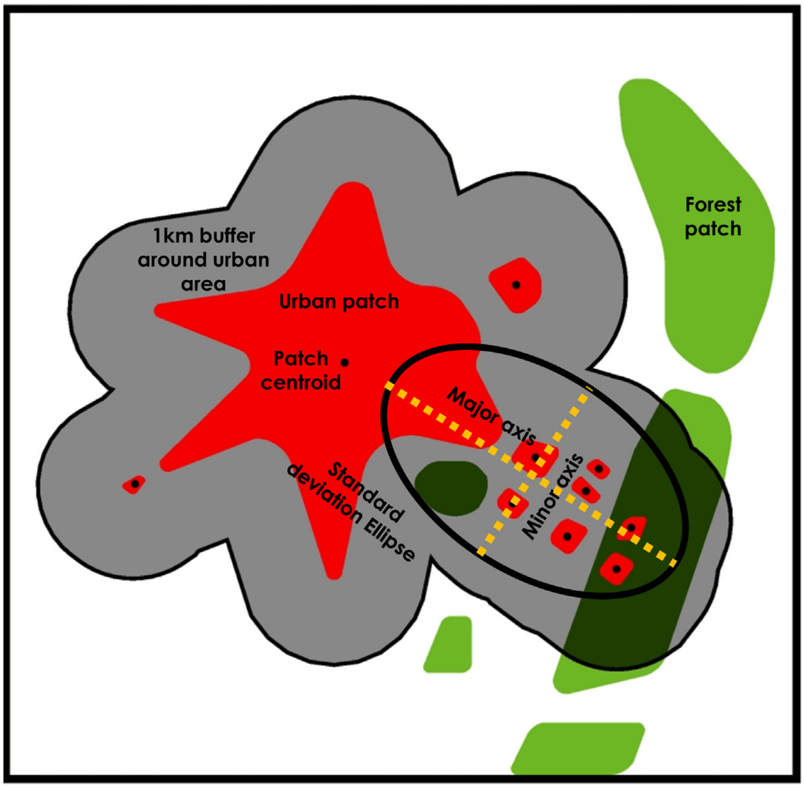



**Fig. 1.** AQI exceedance days by type of pollutant.




$$Total\ Urban\ Area\ A_C = \sum_{i \in C} a(P_i)$$

$$Patch\ Number\ n = \sum_{i \in C} i$$

$$Mean\ Urban\ Patch\ Size\ M_C = \frac{A_c}{n}$$

$$Patch\ Size\ Standard\ Deviation = \sqrt{\sum_{i \in C} \frac{(a(P_i) - M_C)^2}{n-1}}$$

$$Urban\ Forest\ Mixing = \sum_{i \in c} \frac{a(\bigcup_{i \in C} B(P_i) \cap F_i)}{A_c}$$

$$Eccentricity = \sqrt{1 - \left(\frac{semi\ minor\ axis}{semi\ major\ axis}\right)^2}$$

**Fig. 2.** Schematic illustration of metrics. C is the county, P is urban patch, F is forest patch a(.) is area, B(.) is buffer.

network from National Highway Planning Network version 2.1 published by the Bureau of Transportation Statistics as part of the National Transportation Atlas Database, the links were buffered based on number of lanes. This land cover data was reclassified based on the intersection with the buffered road network. In Urban Areas (UA) as designated by US Census 2000, the road classification is treated as urban as roads were considered part of the urban fabric. Outside the UAs, the roads are not treated as urban. Differences in the accuracy of the vector and raster road networks (e.g. curves in the roads) lead to small erroneous residual urban patches in rural areas. To reduce this error, all urban patches are shrunk by replacing them with the value of the cell that is most frequent in its neighborhood, effectively reducing the boundaries. To partially reverse this process, the urban patches are then expanded by the same amount. This twin process has an effect of preserving the larger urban patches while eliminating spurious small patches as the shrinking will render very small urban patches as non-urban and they are no longer expanded in the next step. We experimented with a variety of shrink and expand cell sizes and this method provided the most empirically satisfactory results. The effect of the process is marked in rural counties where the number of patches as well as the size of the patches significantly decrease whereas mixed urban counties see a marked increase in the number of patches (see Fig. 3). The procedure also sharply attenuates the right tails of the distributions of number of patches and size of patches. Python scripts using the ESRI (2011) engine were used to process the land cover data. As counties can be processed independent of one another, naive parallelization is applied to generate the dataset in a reasonable amount of time.

Once the urban patches are identified, the urban form and mixing metrics are calculated using FRAGSTATS (McGarigal & Marks, 1995) and 'aspace' (Bui, Buliung, & Remmel, 2012). The main urban form metrics are number of patches, mean patch area and standard deviation of patch areas, eccentricity of the standard deviation ellipse (SDE) (see Fig. 2). High number of patches, *ceteris paribus*, reflects a fragmentary pattern. Low mean area is reflective either of rural character or high fragmentation of the county. High standard deviation is indicative of satellite townships around a large urban core. An SDE is a representation of directional distribution of the urban form and is calculated using the centroid of patches (Ebdon, 1985). High eccentricity of the SDE is representative of more linear growth patterns (e.g. along rivers and valleys), which are associated with longer trips (Bento et al., 2005) and therefore poor air quality.

In addition to urban landscape metrics, the extent and configuration of forest land was accounted for in our analysis. For each urban patch, we buffered it by 1 km and calculated the area of the forested land within the buffer. The ratio of this forested land to the total urban area in the county is referred to as urban forest mixing (see Fig. 2). This metric accounts not only for proximate forest but is a better metric than standard interspersion and juxtaposition metrics. High values of interspersion and juxtaposition metric occur when urban and forest cells are in a checkerboard pattern, not when clumps of forests are next to clumps of urban areas. Our indicator has high values in both situations. The indicator is dependent on both the fragmentation of urban areas and presence of forests. In places like Texas, where there is relatively little forest, high fragmentation does not result in greater proximate forest cover, whereas in North Carolina it does (Fig. 4).

### *3.3. Statistical models*

Standard analyses use Ordinary Least Squares linear regression to tease out empirical relationships between dependent and independent variables. However, this method is not useful in this particular case because of the presence of spatial autocorrelation. Moran's I for AQI exceedance days of PM2.5, $O_3$ and any CAP, are 0.25, 0.52 and 0.45 respectively, and all of them are statistically significant. Furthermore, the residuals of the linear models are also spatially autocorrelated with values ranging from 0.21 to 0.43 and

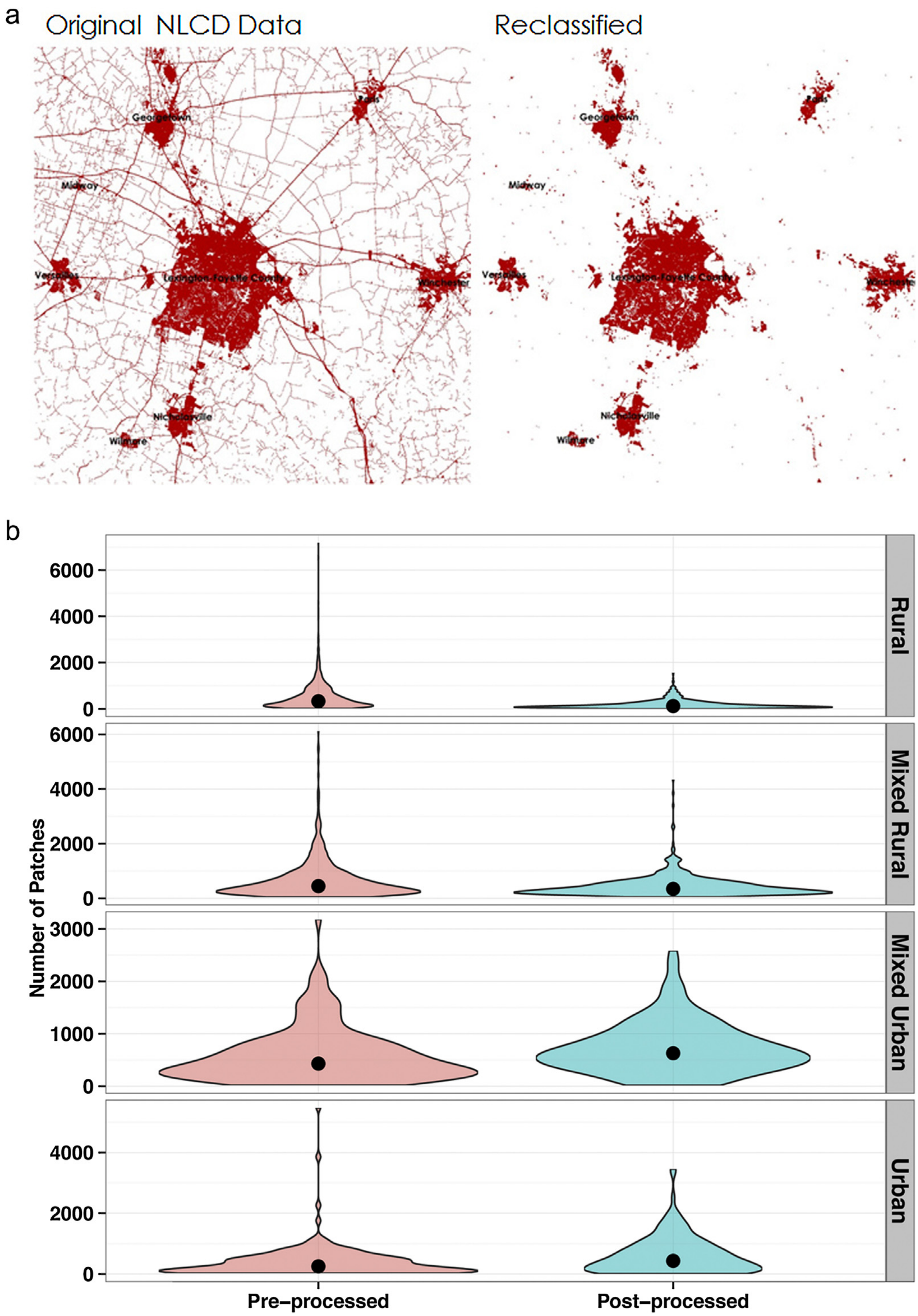



**Fig. 3.** Example of (a) urban land cover (b) distributional difference in a metric, before and after processing the data.

are all significant. To correct for the spatial autocorrelation bias, we use spatial econometric models. There are two types of model specifications in vogue: spatial lag model and spatial error model. The particular model for each pollutant is chosen based on the Lagrange Multiplier test. The formal model specifications are

$$\begin{aligned} Y &= \alpha + \beta X + \rho W Y + \epsilon \quad (\textit{Spatial lag model}) \\ Y &= \alpha + \beta X + \epsilon + \lambda W \xi \quad (\textit{Spatial error model}) \\ \epsilon &\sim N(0, \sigma^2 I) \end{aligned} \tag{1}$$

where $Y$ is the dependent variable (number of AQI exceedances), $X$ is the set of independent variables (urban form metrics as well as control variables), and $\xi$ is the spatial component of the error term. $W$ is the spatial weights matrix that is reflective of the spatial interaction (first order queen contiguity in this case). The coefficients $\alpha$, $\beta$, $\rho$ and $\lambda$ are estimated using a Maximum Likelihood Estimation using 'spdep' (Bivand, 2013) in R (R Development Core Team, 2009). Table 2 provides the descriptive statistics of the variables used in the model, while Table 3 summarizes the expected signs for the relationship between air quality

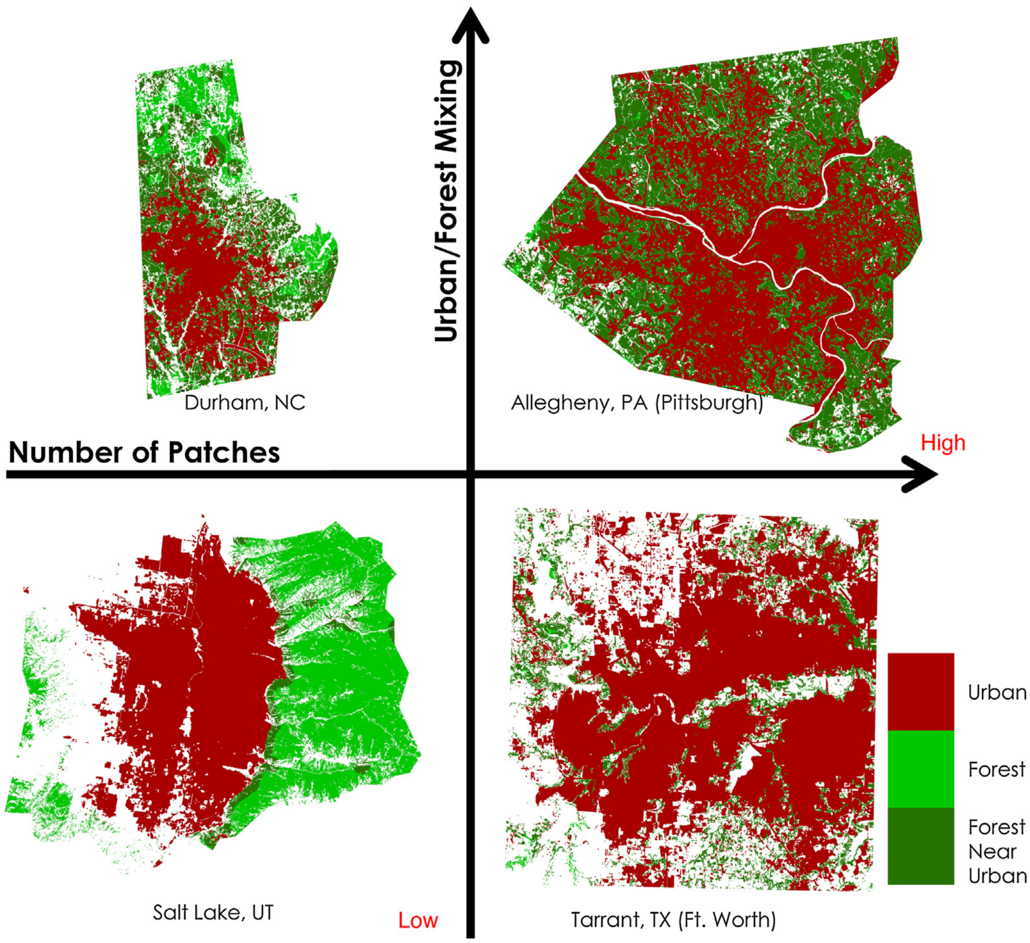



**Fig. 4.** Examples of different types of urban patterns in the US.

and various urban form indicators and the justifications for those relationships.

## 4. Patterns of urban form & air quality – a description

In this section, we briefly describe patterns of urban development as seen from the perspective of combinations of different indicators. Fewer patches combined with large urban areas in a county is reflective of contiguous development whereas small mean patch area with low standard deviation is reflective of fragmentary development. Counties that form the core of metropolitan regions (e.g. Suffolk for Boston) have contiguous urban areas whereas outer suburbs and some mixed rural counties exhibit fragmentary urban pattern evidenced by large number of patches and low mean patch area. The core counties also have the high standard deviation because the large contiguous urban areas surrounded by smaller satellite developments. Regions that urbanized earlier in the century (Boston, Chicago, New York, etc.) are more contiguous while regions that have urbanized later in the century (Phoenix, Houston, Raleigh, etc.) exhibit fragmentary development (Fig. 5).

However, not all the patterns can be explained by the novelty of infrastructure and suburbanization in the Sunbelt. County boundaries and sizes have a significant impact on the indicators. Small core counties, such as Virginia's city-counties (Alexandria,

**Table 2**
Descriptive statistics.

| Statistic | Mean | St. dev. | Min | Max | *n* |
|---|---|---|---|---|---|
| Number of urban patches | 324.44 | 355.73 | 5 | 4352 | 3097 |
| Mean urban patch area (sq. km) | 0.20 | 0.62 | 0.01 | 16.14 | 3097 |
| Total urban area (sq. km) | 66.46 | 160.06 | 0.14 | 3164.30 | 3097 |
| Std. dev of urban patches (sq. km) | 1.84 | 5.06 | 0.002 | 101.22 | 3097 |
| Eccentricity of SDE | 0.74 | 0.16 | 0.13 | 1.00 | 3097 |
| Total forest area (sq. km) | 641.56 | 996.21 | 0.00 | 15,733 | 3097 |
| Forest mixing | 6.82 | 12.24 | 0.00 | 149.89 | 3097 |
| Population (000s) | 96.53 | 311.08 | 0.081 | 9785.3 | 3097 |
| Median income (USD) | 43,459 | 11,410.2 | 18,869 | 113,313 | 3097 |
| Centrality (Gini) | 0.58 | 0.16 | 0.00 | 0.91 | 3088 |
| Proportion industrial employment | 0.20 | 0.09 | 0.00 | 0.66 | 3045 |
| Average summer daily max. temperature (°C) | 26.4 | 3.4 | 16.0 | 38.4 | 2750 |
| Total annual precipitation (cm) | 175.7 | 71.7 | 1.7 | 639.5 | 2952 |
| Exceedance days (any CAP) | 9.4 | 15.6 | 0 | 156.7 | 1139 |
| Exceedance days ($O_3$) | 6.8 | 10.3 | 0 | 116.2 | 781 |
| Exceedance days (PM2.5) | 2.0 | 4.3 | 0 | 48.6 | 697 |

**Table 3**
Expected signs in the statistical models.

| Variable | Sign | Justification |
|---|---|---|
| Number of urban patches | + | Increase in fragmentation results in poor air quality |
| Mean urban patch area | – | More contiguous development results in better air quality |
| Total urban area | +/0 | More urban counties have worse air quality. However, some studies did not find any relationship |
| Std. dev of urban patches | + | Higher std. dev. is indicative of fragmentation at the fringes and therefore poor air quality Increase in fragmentation results in poor air quality |
| Eccentricity of SDE | + | Longer travel times and therefore poor air quality |
| Total forest area | +/–/0 | Increase in biogenic emissions, increase in pollutant reduction potential |
| Forest mixing | – | Better air quality from proximate forests |
| Population | + | Higher levels of population reflects increased economic activity |
| Median income | – | Richer regions have better air quality |
| Centrality (Gini) | – | Uneven density results in concentrations of people and therefore higher air quality |
| Proportion industrial employment | – | Higher emissions from point sources |
| Average summer daily max. temperature | + | Hotter places have worse air quality |
| Total annual precipitation | – | Precipitation removes pollutants |

Fredricksburg, etc.), have large average patch sizes and look more contiguous than their surrounding counties. Likewise, geographic features such as coastlines, wetlands, or topography do have some role in explaining the urban patterns. The hills and waterways of Seattle sever development and increase fragmentation while the coastal wetlands of Louisiana seem to coalesce the urbanization. Conversely, in rural Iowa and Western Texas, development is not restricted by geographic features, yet still seem to exhibit high degree of fragmentation. These areas are not rapidly growing nor are they within large metropolitan areas. Oil wells and associated

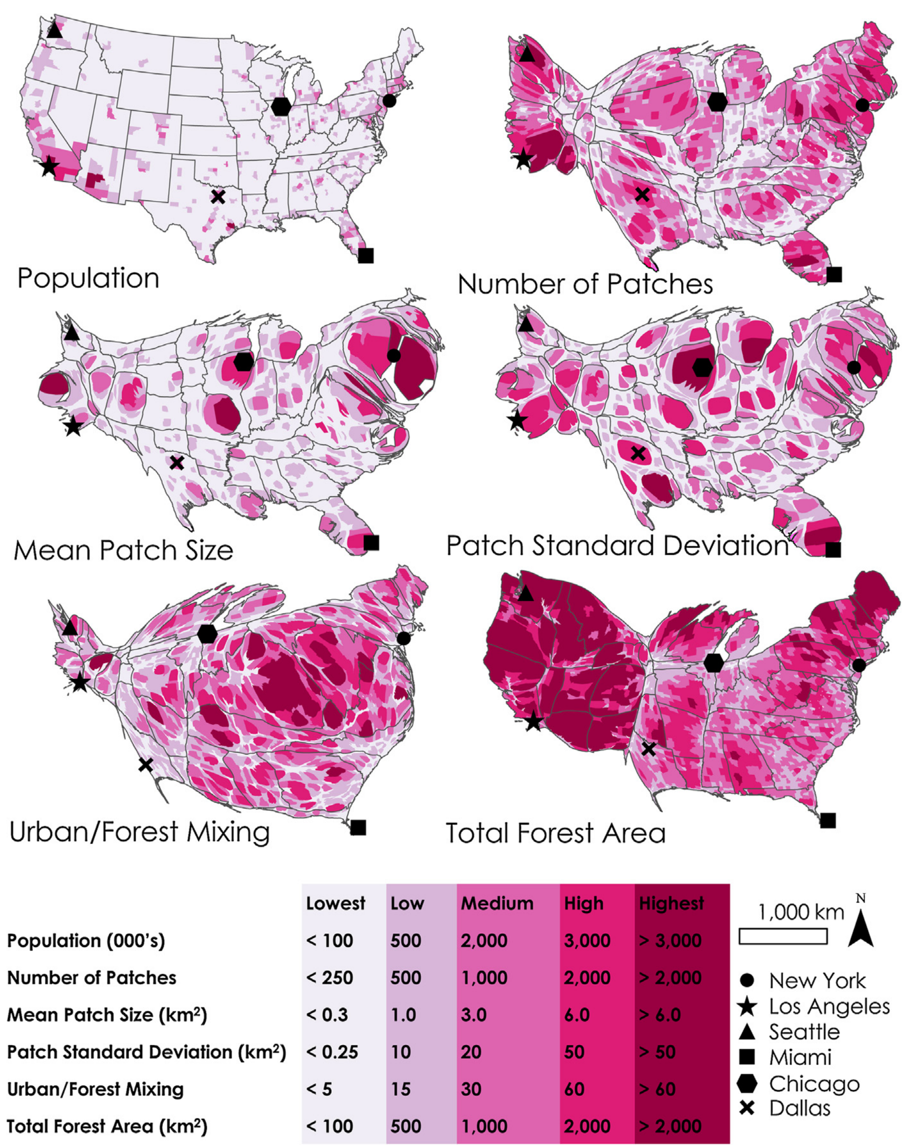



**Fig. 5.** Cartograms of different urban indicators.

infrastructure in Texas and impervious agricultural operations in Iowa explain the fragmentary urban patterns. These two cases point to the advantage of urban landscape metrics that are not captured by the population based indicators.

In the US, the wilderness areas determine the forested landscape. The most prominent of these are located in the Rocky Mountain, Pacific Northwest Coast, Appalachia and Northern New England regions. The High Plains region, Gulf Coast and the Mississippi River Valley contain very little forest area. Overall, the pattern of urban-forest mixing is highest in counties with very little urban land that is highly interspersed with forest cover; Appalachian counties have particularly high ratios (Fig. 5). Urban-Forest mixing is generally higher in the Pacific Northwest and inland eastern counties where forest coverage is highest along with urbanization.

Exceedances of any CAP are less than 10% of days in most of the Northeast counties. On the other hand, the distribution of the exceedances for any CAP days has a long right tail for the mixed rural counties in the West. Southern California and the Central Valley suffer from the most air quality exceedances for all pollutant categories. On the east coast, the metropolitan corridor around Philadelphia and New York City suffers from lower air quality. Exceedances for PM2.5 seem to be slightly more prevalent in West Coast and Rocky Mountain states, with the exception of Pittsburgh, PA and Birmingham, AL. The north-western quadrant of the country, spanning from Wisconsin to Washington, experiences very few $O_3$ exceedances suggesting the strong role of high summer temperature for this pollutant.

Although there is a correlation between development and air quality, population and urban land area alone are not sufficient for explaining the exceedances. The most populated counties in the nation are not the ones which experience the most exceedances nor do the counties with the largest urban area necessarily experience worse air quality. The heavily developed counties in southern Florida and metropolitan New York rank far lower in AQI exceedances than their urban development would suggest. Many rural counties with fairly low populations and little developed land area have surprisingly poor air quality. In fact, some of the counties that have the highest proportion of AQI exceedance days are mixed rural counties in the Western United States (Fig. 1). Of all the rural and mixed rural counties, the Western counties have the highest proportion of $O_3$ exceedance days.

**Table 4**
Results of statistical models for all counties.

| | Dependent variable: number of days with AQI > 100 | | |
|---|---|---|---|
| | Particulate matter | Ozone | Any CAP |
| Observation days | 0.02$^{***}$ | 0.01$^{*}$ | 0.03$^{***}$ |
| | (0.002) | (0.004 | (0.004) |
| Total urban area (log) | −1.37$^{***}$ | −4.58$^{***}$ | −4.49$^{***}$ |
| | (0.44) | (0.88) | (1.12) |
| Number of patches | 0.002$^{***}$ | 0.01$^{***}$ | 0.01$^{***}$ |
| | (0.0004) | (0.001) | (0.001) |
| Total land area (log) | −0.08 | −0.95$^{**}$ | −1.11$^{*}$ |
| | (0.21) | (0.47) | (0.60) |
| Mean urban patch area (sq. km) | −0.001 | −0.97$^{*}$ | −1.30$^{*}$ |
| | (0.23) | (0.50) | (0.78) |
| Std. dev of urban patch area (sq. km) | 0.06$^{**}$ | 0.24$^{***}$ | 0.53$^{***}$ |
| | (0.03) | (0.06) | (0.09) |
| Eccentricity of SDE | 0.60 | 0.65 | 2.22 |
| | (0.92) | (1.89) | (2.62) |
| Total forest area (log) | 0.13 | 0.33$^{*}$ | 0.41 |
| | (0.09) | (0.19) | (0.26) |
| Urban forest mixing | −0.09$^{**}$ | −0.17$^{***}$ | −0.20$^{***}$ |
| | (0.04) | (0.06) | (0.07) |
| Population (log) | 0.82$^{**}$ | 2.88$^{***}$ | 2.45$^{**}$ |
| | (0.41) | (0.81) | (1.07) |
| Median income (log) | −2.41$^{***}$ | −1.11 | −4.93$^{**}$ |
| | (0.76) | (1.47) | (2.05) |
| Centrality | −0.94 | −5.86$^{**}$ | −0.90 |
| | (1.44) | (2.79) | (3.57) |
| Proportion of industrial employment | 3.42$^{*}$ | 12.53$^{***}$ | 17.22$^{***}$ |
| | (1.96) | (3.97) | (5.13) |
| Mean summer temperature (°C) | −0.07 | 0.14 | 0.21$^{*}$ |
| | (0.05) | (0.10) | (0.13) |
| Precipitation (cm) | −0.01$^{***}$ | −0.01 | −0.01 |
| | (0.002) | (0.004) | (0.01) |
| $\rho$ | 0.19$^{***}$ | 0.42$^{***}$ | 0.37$^{***}$ |
| | (0.04) | (0.29) | (0.27) |
| Observations | 639 | 707 | 1033 |
| Nagelkerke $R^2$ | 0.39 | 0.39 | 0.48 |

$^{*}$ $p < 0.1$.
$^{**}$ $p < 0.05$.
$^{***}$ $p < 0.01$.

## 5. Results

$\rho$ is statistically and substantively significant (Table 4), validating the need for spatial models. The models also have modest predictive power (pseudo-$R^2 \sim 0.4$). Both the Likelihood Ratio tests and the Information Criteria suggest that the spatial models are more useful than the standard linear models. Heteroskedasticity remains a problem even after accounting for the spatial autocorrelation. However, the use of robust standard errors does not change the significance or the general thrust of the results; we do not present them for concision. It should also be noted that climate variables such as temperature and precipitation were not significant in many of the models and therefore are not presented in detail. The main issue is the significant spatial autocorrelation in the climatic variable relative to the dependent variables. As expected locations with higher temperatures have more AQI exceedance days and locations with greater precipitation have fewer.

The demographic control variables in the models behave as expected. Increases in county population results in decreased air quality. Increases in the number of observation days increases the number of days AQI is greater than 100. Industrial employment (manufacturing, mining, utilities, construction, etc.) has an expected negative effect on air quality. However, the coefficients should be treated with caution relative to other coefficients because the variable is a ratio between 0 and 1, where as urban form variables are levels that have a much higher range (see Table 2). Wealth of a county measured by median income has a negative effect on PM2.5 days and overall exceedance days. It is likely that higher incomes translate to less polluting automobiles and stricter emission control mechanisms. Controlling for all these variables, the urban form indicators seem to play a separate role.

The results of the statistical models provide evidence for some of the hypotheses. Fragmentary urban patterns described by high number of urban patches are positively associated with increase in number of days where AQI is above 100 and the result is statistically significant for all types of pollutants considered here. An increase in the amount of the proximate forest reduces the number of low air quality days. Increasing presence of forest area leads to higher number of days with ozone exceedances as well due to their production of ozone.

To test whether the results are significantly biased by the presence of rural counties we took a subsample of Metropolitan counties based on Office of Management and Budget (2000)'s definition. It should be noted that this definition of Metropolitan counties does contain relatively rural counties though their number is sharply reduced. While the models have similar explanatory power as the models with all counties, the statistical significance and the direction of the relationship of the variables did not change except in a few instances (Table 5). Total number of observation days is no longer significant for $O_3$ model and urban forest mixing is no longer significant for PM model. Within the metropolitan

**Table 5**
Results of statistical models for counties in metropolitan areas.

| | Dependent variable: number of days with AQI > 100 | | |
|---|---|---|---|
| | Particulate Matter | Ozone | Any CAP |
| Observation days | 0.02*** | 0.01 | 0.04*** |
| | (0.003) | (0.01) | (0.01) |
| Total urban area (log) | −2.09*** | −5.45*** | −7.38*** |
| | (0.78) | (1.33) | (1.97) |
| Number of patches | 0.003*** | 0.01*** | 0.01*** |
| | (0.001) | (0.001) | (0.002) |
| Total land area (log) | −0.01 | −0.90 | −1.82* |
| | (0.36) | (0.67) | (0.98) |
| Mean urban patch area (sq km) | −0.003 | −0.99* | −1.67* |
| | (0.30) | (0.59) | (0.98) |
| Std. dev of urban patch area (sq km) | 0.07* | 0.27*** | 0.57*** |
| | (0.04) | (0.07) | (0.11) |
| Eccentricity of SDE | 0.70 | 1.46 | 1.16 |
| | (1.35) | (2.46) | (3.97) |
| Total forest area (log) | 0.17 | 0.40 | 0.62 |
| | (0.14) | (0.25) | (0.38) |
| Urban forest mixing | −0.11 | −0.31** | −0.40** |
| | (0.08) | (0.13) | (0.16) |
| Population (log) | 1.44** | 2.83** | 4.80** |
| | (0.73) | (1.25) | (1.95) |
| Median income (log) | −2.48** | −1.49 | −9.23*** |
| | (1.18) | (1.93) | (3.11) |
| Centrality | 0.42 | −10.25** | 1.31 |
| | (2.68) | (5.19) | (7.60) |
| Proportion of industrial employment | 7.47** | 15.29** | 26.52*** |
| | (3.61) | (6.28) | (9.59) |
| Mean summer temperature (°C) | −0.03 | 0.20 | 0.36* |
| | (0.08) | (0.14) | (0.20) |
| Precipitation (cm) | −0.01*** | −0.01 | −0.01 |
| | (0.003) | (0.01) | (0.01) |
| $\lambda$ | 0.20*** | | |
| | (0.05) | | |
| $\rho$ | | 0.39**** | 0.34*** |
| | | (0.03) | (0.03) |
| Observations | 425 | 494 | 596 |
| Nagelkerke $R^2$ | 0.38 | 0.50 | 0.38 |

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

counties, centrality is much more highly significant; concentrating all the county population into a single block group reduces the $O_3$ exceedances by 10 days (as opposed to 6 in all counties model). Even within the metropolitan counties, increasing urban area while holding population constant reduces the number of days with AQI > 100, while increasing standard deviation increases them. Fragmentation and satellite greenfield development are associated with decreases in air quality. This suggests the analyses are relatively robust and the relationships between the landscape metrics and air quality are largely generalizable irrespective of the level of development.

## 6. Discussions

Higher fragmentation at the fringes, as evidenced by larger number of patches, decreases air quality. Increases in the mean area of urban patches are not associated with PM2.5 but are associated with fewer $O_3$ and overall exceedance days. The standard deviation seems to have a more consistent effect on all types of pollutants including PM2.5 and $O_3$. A greater variation in the sizes of patches is associated with more AQI exceedance days. The presence of small satellite urban areas near but not contiguous to large urban areas increase the number of AQI exceedance days. The joint effect of these three variables suggests that contiguous urban development is associated with better air quality.

Interestingly, increasing urban area while controlling for the population reduces the number of AQI exceedances. A percent increase in urban area leads to a reduction of AQI exceedance days between 1.3 and 4.5 depending on the pollutant in question. This seems to counter the claims that decrease in density results in higher travel volumes and therefore lower air quality. An explanation might be that urbanization actually reduces biogenic emissions and in some cases even low density urbanization might improve air quality.

Another possibility is that per capita developed land consumption is higher in rural counties which in general have better air quality (Fig. 1). To investigate if this is the case we examined the bivariate relationship between the proportion of AQI exceedance days and per capita consumption of developed land (see Fig. 6). Unsurprisingly, the result is dominated by the fact that rural counties have better air quality even when the per capita urban land consumption is higher. In relatively urban counties, the relationship is more heterogeneous. In mixed urban counties, lowering the density increases air quality before decreasing it again. In the urban counties with highest per capita land consumption, only Lake County, OH (Cleveland) exceeds AQI standards for more than 15% of its observation days. Two different explanations can be suggested for these results: one is that air quality effects of low-density development are not limited to their boundaries. Alternatively, geographic scale of both air quality, demographic and urban form metrics matter and likely suffer from Modifiable Areal Unit Problem. In other words, low density metropolitan areas do not necessarily correspond to low-density counties or cities and air quality in each of these places is heterogeneous. The impact of a fragmented landscape might manifest not in the fragmented county but where that pattern creates congestion. These explanations require further investigation.

The centrality measure also has a surprising relationship to air quality. Unequal distribution of population in a geographic region is thought to promote sustainable living because of economies of scale and scope. However, the centrality (Gini coefficient of population density) has a significant effect only in the $O_3$ model. Moving a county from a uniform population density distribution (0) to concentrating the density in one block group (1), reduces $O_3$ exceedance days by 5.8.

Centrality, however, does not seem have a relationship with air quality in general. This appears contrary to the results of Clark et al. (2011) who found centrality of population in a metropolitan region to be negatively associated with emissions. It is useful to remember, though, that centrality in Bento et al. (2005) and Clark et al. (2011) is based on the central business district of a metropolitan region, which does not account for polycentric regions. Furthermore, the Gini index of the population density within a county is quite different from that of the metropolitan regions. Within counties, rural counties exhibit high Gini index (median 0.65), whereas urban counties exhibit lower index (median 0.40). This result is due to rural counties having small pockets of population surrounded by large uninhabited areas while urban counties have relatively uniform distribution. This suggests that population centrality measures are scale variant. Controlling for the size of the population and the relative urbanity of the county, the distribution of population density is not associated with overall air quality but is associated with $O_3$.

The directional distribution of the point patterns of the urban areas seem to have no effect on the air quality. Neither the eccentricity nor the length of the major and minor axes of the SDE (not shown in tables) or the standard distance (not shown) are associated with air quality. The bivariate plots indicate that while the eccentricity is not correlated with air quality there is a differential correlation of minor axis and air quality depending on county type. However, the relationship disappears when controlled for other

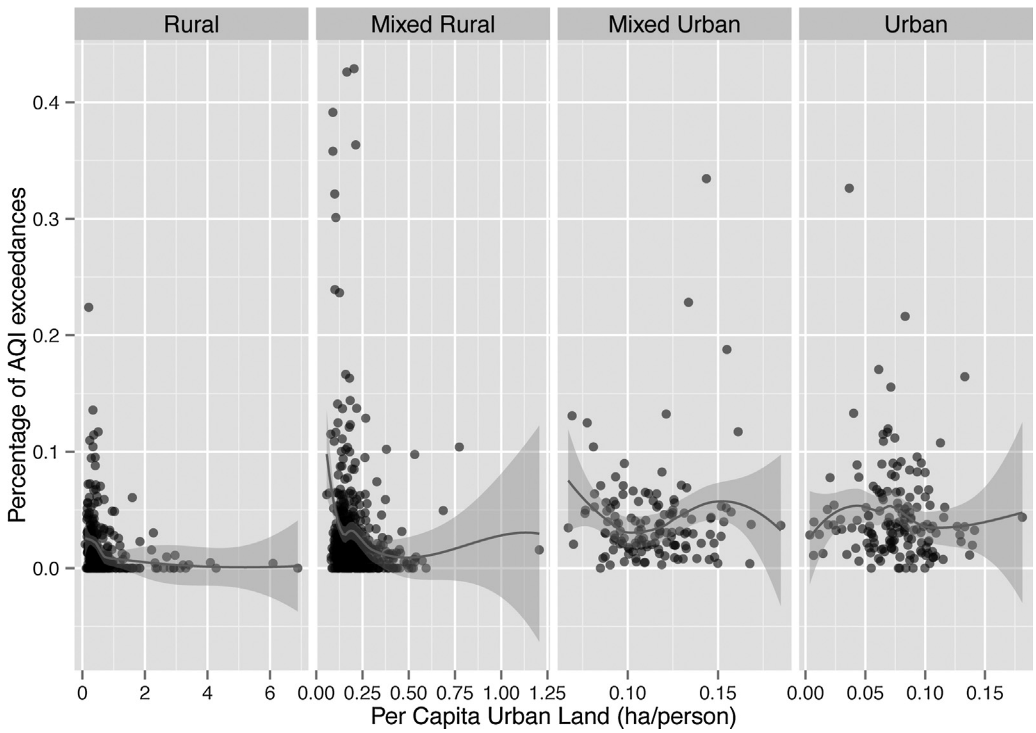



**Fig. 6.** Heterogenous relationship between urban land consumption and air quality (any CAP). The trend line is a LOESS smoother.

variables. This suggests that directional distribution is not as important as the fragmentation pattern itself. This finding is consistent with the finding about the city shape's influence on air quality in Clark et al. (2011).

Previous studies have established some aspects of the relationship between urban form and air quality, however, few of these have considered the effects of interspersed urban and forest lands. The presence of more forest lands in a county contributes to $O_3$ exceedance days. On the other hand, the presence of proximate forests is significantly associated with improved air quality controlling for other variables. This suggests that while fragmentary urban form is undesirable from the emissions perspective, it is much more undesirable in areas without forest cover. As agricultural land is easier to convert into urban land, many greenfield developments are in agricultural zones. If a fragmentary pattern of urban development must be pursued, preserving the forested areas would help mitigate the pollutants.

## 7. Caveats & further research

Simple descriptive analysis of the AQI suggests that air quality is an issue even beyond metropolitan areas. Thus, using datasets that have wide geographic coverage is important to understand the relationship between urban form and air quality. Further research could examine how the changes in development patterns over time impact air quality and be used to fashion land use policies that may improve air quality. The results of this analysis provide some insights into the relationship between urban form and air quality in the US, however, several caveats should be considered including influence of the scale, quality of the datasets, the implied causal mechanisms and the artifacts of indicator construction. We detail a few of them below.

The definitional problem of using a measurement from one location as the air quality for the entire county probably belies a more heterogeneous picture of air quality and perhaps even exposure within a county. Additionally, very few climatic variables are considered in this empirical analysis. The atmospheric chemistry and transport models could also be used to model the air quality to better capture the spillover effects.

Along with the chemical transport process, the presence of point sources of pollution affects air quality in the region. In this study, we proxy the point sources by the amount of industrial employment in a county. We find that the higher the proportion of industrial employment within a county, the worse the air quality. However, comparing the standardized coefficients of the regression (not shown in tables), the urban form variables have five times the explanatory power as the industrial proportion variables suggesting the relative importance of non-point sources for air quality. However, there might be other point sources of pollution that are unaccounted for by this measure. Warehouses, for example, employ relatively few but still are attractors of large freight volumes are not adequately accounted for in this research. Furthermore, industrial activity itself might be endogenous with urban form variables; suburban and exurban industrialization is a fragmentary urbanization process as urban deindustrialization pattern continues in the US (Lester, Kaza, & Kirk, 2014). Further research should explore these connections.

Similar to the air quality data, there is some concern as to the accuracy of the land cover data. A comprehensive evaluation the 2006 NLCD data determined that the accuracy was 84% (Wickham et al., 2013). In particular, developed open space class is often misclassified as pasture or other non-urban uses. This potentially introduces bias in urban indicators. Another avenue for research is to disaggregate the urban classes and measure how the composition and configuration of low density versus high density urban affect air quality.

We did not fully account for the tree cover within urban areas as we have considered only the interspersion of forest and urban land cover classes. Future studies could use Normalized Difference Vegetation Index (NDVI) or Leaf Area Index to fully understand the effect of trees. Some vegetation mixed with pervious surface is classified as urban in the land cover datasets. Finer grained analysis at neighborhood levels could account for nuances in interspersion of vegetation and urban development. Trees might have much more local effects on air quality at the street and neighborhood level that is not adequately captured by a few monitors interspersed on top of buildings in a county.

Another factor that influences the metrics and the analysis is the scale. As mentioned earlier, many of the urbanization metrics used in this paper are scale variant and suffer from the Modifiable Areal Unit Problem. One of the advantages of using counties as units is that their boundaries, unlike metropolitan regions or city boundaries, are relatively stable and could be used to study patterns of urbanization and air quality over time. However, it is important to replicate and verify these findings at different geographic scales.

This analysis focused on air quality as measured by the AQI. From a public health perspective, exposure may be more important than the air quality. Therefore, it is necessary to extend these studies to include differential exposure and risk to different groups (Rissman, Arunachalam, BenDor, & West, 2013; Schweitzer & Zhou, 2010). Local air quality at a street and neighborhood scale is dependent on urban form at a street level and determines urban canyons, local vegetation characteristics and surface temperature. Exposure studies should focus on micro level design interventions that may help mitigate pollutant impacts to high risk groups. Finally, this study only assessed annual emissions; variations due to seasonality of economic activity and commuting patterns could be explored.

## 8. Conclusions

This study contributes to research on air quality and urban form by examining the relationships beyond metropolitan regions. Previous work has relied on limited data and ignored rapidly urbanizing rural and mixed rural counties. Urban form indicators that are used in this study are complementary to the ones that are used in other research. We find that after controlling for demographic factors and the level of urbanization, both the pattern of urbanization and the mixing of different land cover types are important correlates of pollutant levels and air quality. Public action for mitigating pollutant levels could refer to land use strategies in addition to other emission control mechanisms.

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