

Predicting citywide distribution of air pollution using mobile monitoring and three-dimensional urban structure

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ARTICLE INFO

Keywords:

Air pollution
STURLA
Urban structure
Mobile monitoring
Spatial prediction

ABSTRACT

Understanding relationships between urban structure patterns and air pollutants is key to sustainable urban planning. In this study, we employ a mobile monitoring method to collect PM_{2.5} and BC data in the city of Philadelphia, PA during the summer of 2019 and apply the Structure of Urban Landscapes (STURLA) methodology to examine relationships between urban structure and atmospheric pollution. We find that PM_{2.5} and BC vary by STURLA class, and some classes exhibit significant difference in pollution concentrations. We also find that the proportions in which STURLA components are present throughout the urban landscape can be used to predict the spatial distribution of urban air pollution. Among frequently sampled STURLA classes, *gpl* (grass, pavement, and low-rise buildings) hosted the highest PM_{2.5} concentrations on average ($16.60 \pm 4.29 \mu\text{g}/\text{m}^3$), while *tgwbp* (trees, grass, bare soil, water, pavement) hosted the highest BC concentrations ($2.31 \pm 1.94 \mu\text{g}/\text{m}^3$). Furthermore, STURLA combined with machine learning modeling was able to correlate PM_{2.5} ($R^2 = 0.68$, RMSE $2.82 \mu\text{g}/\text{m}^3$) and BC ($R^2 = 0.64$, RMSE $0.75 \mu\text{g}/\text{m}^3$) concentrations with urban landscape composition and interpolate concentrations throughout the city. These results demonstrate the efficacy of the STURLA methodology in modeling relationships between air pollution and urban structure patterns.

1. Introduction

Population growth in urban areas is increasing rapidly; the United Nations projects that 68% of the world's population will live in urban areas by 2050 (United Nations, Department of Economic and Social Affairs, Population Division 2019). As urban areas expand, a larger proportion of the global population will be exposed to increasingly high and potentially harmful levels of air pollution; identifying and mapping where these pollutants are is key to developing sustainable cities. At present, approximately 3.7 million premature deaths worldwide can be attributed to elevated air pollutant concentrations each year (Cohen et al., 2017). Air pollutants disproportionately impact vulnerable populations based on race, (Gray et al., 2013; Perlin, Sexton, & Wong, 1999; Perlin, Wong, & Sexton, 2001, gender and sexual orientation (Collins et al., 2017a, 2017b) and socioeconomic status (Gray et al., 2013; Perlin et al., 1999; Zhou et al., 2011). It is crucial that we understand how air pollutants interact with complex urban structures to identify how cities can be designed with a human health focus.

Particulate matter (PM) has been linked to negative health outcomes,

including asthma (Anenberg et al., 2018; Halonen et al., 2008; Rabinovitch et al., 2006) lung cancer (Hamra et al., 2014; Pope et al., 2002), DNA alteration (Baccarelli et al., 2009; Sørensen et al., 2003; Shi et al., 2019), and disrupted lung (Shakya et al., 2016) and immune functions (Honda et al., 2017; Zelikoff et al., 2003). Polluted air also host potentially pathogenic bacteria for humans (Liu et al., 2018; Stewart et al., 2020) and viruses (Zhu et al., 2020) that could potentially alter the human lung microbiome (Stewart & Kremer, 2021; Willis et al., 2020). Fine particulate matter (PM_{2.5}) is of particular concern due to its prevalence in urban atmospheres. A subset of PM_{2.5}, black carbon (BC) is formed through incomplete combustion of fossil fuels and is particularly prevalent in urban areas. Almost all of BC originates from anthropogenic sources, with biomass fires being the only natural source of BC (Hitzinger & Tohno, 2001); as such, BC is commonly used as an indicator of anthropogenic influence on ambient air pollution (Cyrys et al., 2003; Targino et al., 2016).

Studies of urban air pollution have established relationships between urban structure and ambient air pollution (Eeftens et al., 2012; Wu, Xie, Li, & Li, 2015; Yuan et al., 2019). For example, in Philadelphia PM

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concentration variation across neighborhoods was attributed to differences in open space and land structure (Shakya et al., 2019). The organization and height of buildings, barriers and other structures in an urban environment can influence air flow, which in turn impacts PM dispersal locally (Baldauf et al., 2016; Gallagher et al., 2015; Ng & Chau, 2012; Stewart, Kremer, Shakya, Conway, & Saad, 2021; Yang et al., 2020). Though many urban areas are characterized by dense built environments, different types of urban green space (e.g. urban forest, parks, gardens, and private yards) are an integral part of the urban landscape. Cities are increasingly adopting strategies such as urban greening to counteract environmental degradation and enhance human wellbeing; however, the efficacy of these strategies remains unclear (Nemitz et al., 2020). Vegetation such as trees and grasses have been shown to reduce air pollution by facilitating pollutant deposition and uptake of particulate matter, but they are also capable of causing an increase in local pollutant concentrations through biogenic emissions that facilitate secondary aerosol formation and the inhibition of air flow (Brantley et al., 2014; Chen et al., 2016; Eisenman et al., 2019; Xing & Brimblecombe, 2019).

It is clear that the individual components of urban environments, such as presence of greenspace, influences air pollution distributions. However, the complexity of urban topologies makes it difficult to understand how these individual components interact to influence air pollution at more localized scales. In urban environments, urban structures often change drastically over short distances (Cadenasso et al., 2007). While cities may contain common environmental features, differences in their organization have varied impacts on air quality, further complicating efforts to generalize the impact that urban environments have on air pollution. Thus, defining a geographically meaningful units that can be utilized in reproducible and scalable analyses is paramount to effective urban planning and development.

The Structure of Urban Landscape (STURLA) composite classification allows for modeling of diverse urban processes using the three-dimensional shape of cities at fine spatial scales. STURLA does so by using land cover and building height data to identify common compositions of urban environments that are meaningful for scientists and urban planners (Hamstead et al., 2016). STURLA studies have linked urban landscape structure and land surface temperature (Hamstead et al., 2016; Kremer et al., 2018; Larondelle et al., 2014; Mitz et al., 2020), as well as the phylogenetic diversity of the atmospheric microbiome (Stewart et al., 2021). STURLA allows for classifications of urban structure, that have the potential to reshape our understanding of how the composition and spatial organization of urban environments influence environmental parameters. There have also been efforts to improve the accuracy of urban air pollution measurement, as variability in urban landscape composition can influence pollutant dispersal and affect concentrations at small scales (Abhijith & Gokhale, 2015; Gallagher et al., 2015; Hagler et al., 2012). In recent years, mobile monitoring has emerged as a novel method with which to study the spatiotemporal distribution of air pollutants in urban environments (Apte et al., 2017; deSouza et al., 2020; Deville Cavellin et al., 2016; Shakya et al., 2019; Sm et al., 2019; Targino et al., 2016; Van Poppel et al., 2013), as it can collect data at finer spatial scales than is feasible with stationary monitoring (Shakya et al., 2019; Van den Bossche et al., 2015) and does not rely on interpolation to characterize pollutants throughout a city.

In this study, we use data collected through mobile monitoring to measure concentrations of particulate matter smaller than 2.5 μm ($\text{PM}_{2.5}$) and black carbon (BC) throughout the city of Philadelphia over the course of 12 days during the summer of 2019 (Cummings et al., 2021). We use STURLA (Hamstead et al., 2016) in conjunction with this collected air pollution data to analyze the urban structure-air pollution relationship across the city of Philadelphia. We then use STURLA to predict air pollution patterns and identify drivers of heterogeneity in pollutant concentrations.

2. Methods

2.1. Site description

Philadelphia, Pennsylvania is the sixth-most populous city in the United States of America and the largest city in the state of Pennsylvania, with an estimated population of 1.58 million residents in 2018. Philadelphia is a northeastern U.S. city defined by a dense urban core surrounded by predominantly low-rise residential and commercial districts, city parks, and industrial sectors. Two major rivers flow through the city: the Delaware River, which flows southward into the Delaware Bay and Atlantic Ocean, and the Schuylkill River, which flows southward through the western neighborhoods of Philadelphia. The southern and eastern parts of the city house heavy industry along both riverbanks, while large park areas are found in the western and northern areas of the city. For planning purposes, Philadelphia is divided into 18 different planning districts (Fig. 1, Table A1).

2.2. Philadelphia STURLA

The STURLA profile for Philadelphia was made by joining land cover raster data and building height data from 2017 as in Stewart et al., 2021 (Fig. 1). A fishnet with 120m² pixels was overlaid on the joined land cover / building height raster. STURLA classifications for each cell were determined based on the presence of each urban structure component identified; each letter in the STURLA code represents a different component of the urban environment. Each color within a given pixel color within a STURLA cell indicates a specific combination of different urban structure components: trees (t), grass (g), bare soil (b), water (w), pavement (p), low-rise buildings (1 – 3 stories) (l), mid-rise buildings (4 – 9 stories) (m), and/or high-rise buildings (9+ stories) (h). Philadelphia contains 86 STURLA classes, although most of the city can be characterized by just a few classes; *tgpl* is by far the most common class, describing about 51.7% of Philadelphia. Other common classes include *tgplm*, *tgpl*, *tgplp*, *tgwp*, and *w* (Fig. 1). Letters in the STURLA class code denote the presence of specific features of the urban landscape (Fig. 2).

2.3. Sampling description

$\text{PM}_{2.5}$ and BC data were collected using a mobile monitoring method. A van, equipped with instrumentation measuring geolocation data (Trimble Juno 3B with Trimble R1 GNSS receivers), $\text{PM}_{2.5}$ concentrations (Grimm Portable Laser Aerosol Spectrometer, Model 11-C), and BC concentrations (MicroAeth MA200) was driven along two predetermined routes in Philadelphia. Sampling equipment was set up and calibrated as described in Cummings et al. (2021). Data was captured at different temporal resolutions; GPS data was recorded at every one second interval, BC data was recorded at every five second interval, and PM data was recorded at every six second interval (Table A2).

Driving routes were determined using a stratified random sample of STURLA cells in order to ensure that a representative sample of Philadelphia's STURLA class distribution was captured during the sampling period. Specific points of interest such as United States Environmental Protection Agency (U.S. EPA) Toxics Release Inventory (TRI) sites, EPA air pollution monitoring station sites (Fig. A1), the Philadelphia Water Department's green infrastructure sites, and census tracts with high rates of asthma were also considered in route development. An optimized ~483 km (300 mile) driving route that took STURLA class distribution and points of interest into account was generated using Network Analyst in ArcGIS 10.7.1. This optimized route was divided into two ~241.5 km (150 mile) segments in order to make the routes drivable within a day. Occasional road closures in Philadelphia created slight variability in the routes traveled from day to day.

Sampling occurred over a period of 12 days between June 27 and July 29, 2019; each route was sampled six times. Weather conditions during the sampling days were similar (Weather Underground, 2019;

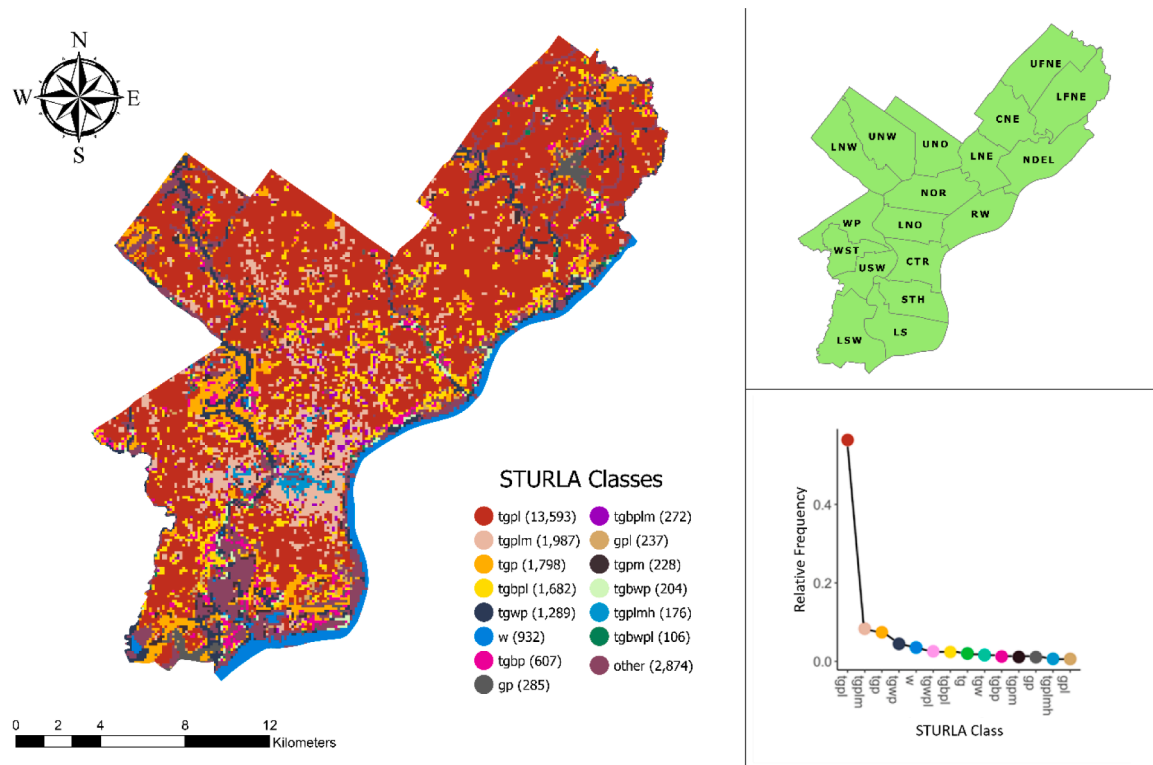


Fig. 1. Map of STURLA classes in Philadelphia, Pennsylvania (left). Classes symbolized include the 14 most sampled classes, which make up 85.5% of Philadelphia; *w* is also included for representation of major waterways. The “other” class consists of the other 72 classes found throughout Philadelphia which, with water, characterize the remaining 14.5% of the city. Also included are Philadelphia’s planning zones (top-right) and a ranked abundance plot (bottom-right) showing relative frequencies of the 14 most abundant STURLA classes throughout Philadelphia. We encourage the reader to download the figure to zoom into specific small text and data they are interested in viewing.

Table A3), with winds throughout the sampling period ranging from 0 – 18 mph (Table A4). Sampling began between 6 – 7 AM on one of the two routes and continued until the entirety of the route was traveled. The daily average vehicle speed ranged from 23.3 – 29.9 km/hr.

2.4. Data analysis

Air pollution and geolocation data were joined by time. For each day of data collection, air pollution data was spatially joined to Philadelphia’s STURLA profile in ArcGIS Pro 2.4; each pixel was assigned the value of the average concentration of all points that fell within it. All cells that contained at least one point were selected and summarized to obtain the average concentration for each STURLA class. The mean concentrations for each class on each day were averaged to determine an average daily mean concentration for each STURLA class for which at least 20 unique cells were sampled; classes that were sampled in fewer than 20 unique cells were summarized into an “other” class for which daily averages were calculated. Permutational t-tests (number of permutations = 10,000) from the “RVAidememoire” package in R were used to determine if differences in the daily mean air pollutant concentrations of STURLA classes were significant, as they take varying sample sizes into account (Hervé, 2020). For each class sampled, the composition of an average cell was determined by finding the mean percentage of all urban structure components for each cell sampled belonging to a specific class. Differences in average STURLA class composition were evaluated using hierarchical clustering based on Bray-Curtis dissimilarities between classes. The clustering dendrogram (Fig. 3) demonstrates compositional similarities between classes; classes with fewer branches separating them are more similar to each other than those with more branches separating them. Likewise, we use hierarchical clustering to demonstrate similarities between daily concentrations in order to better visualize differences in pollutant concentrations

by class.

A supervised machine learning model, Random Forest Regression, was used to investigate the possible distribution of $PM_{2.5}$ and BC in areas not sampled based on measured concentrations and the STURLA landscape components in sampled areas. This method uses an ensemble of weak models that draw a random sample from the original dataset and splits them into a forest of decision trees, which helps to account for spatial autocorrelation and non-linear relationships more effectively than linear models (Oliveira et al., 2012). Using the “caret” package (Kuhn, 2008) in R (3.3.6) (Ihaka & Gentleman, 1996) data were split into 60% training and 40% validation sets that underwent 10-fold cross-validation. The model was trained using the average within-class STURLA urban structure percentages for each class and the mean pollutant concentration measured in that class (e.g. class *tgpl* is the supervised label attached to the mean landscape percentages for *tgpl* across Philadelphia). Root Mean Standard Error (RMSE) was used to assess model error and the model parameters were automatically tuned in *caret* (nTree=500, mtry selected based on best model fit of best mtry value that can be found in provided code for each model). We define validation error as the ratio of predicted to measured concentrations and project it across the city to areas that were not sampled by applying the error for the measured classes to all unmeasured classes. For this the mean air pollutant value per STURLA class was used to estimate the actual concentration. Variable importance is measured as the percent increase in RMSE by removing a variable from the model where once completed for each variable is ranked. Reported correlation coefficients and model error is reported using cross-validated values. Model predictions and results were joined by STURLA class and visualized using ArcMap 10.7.1.

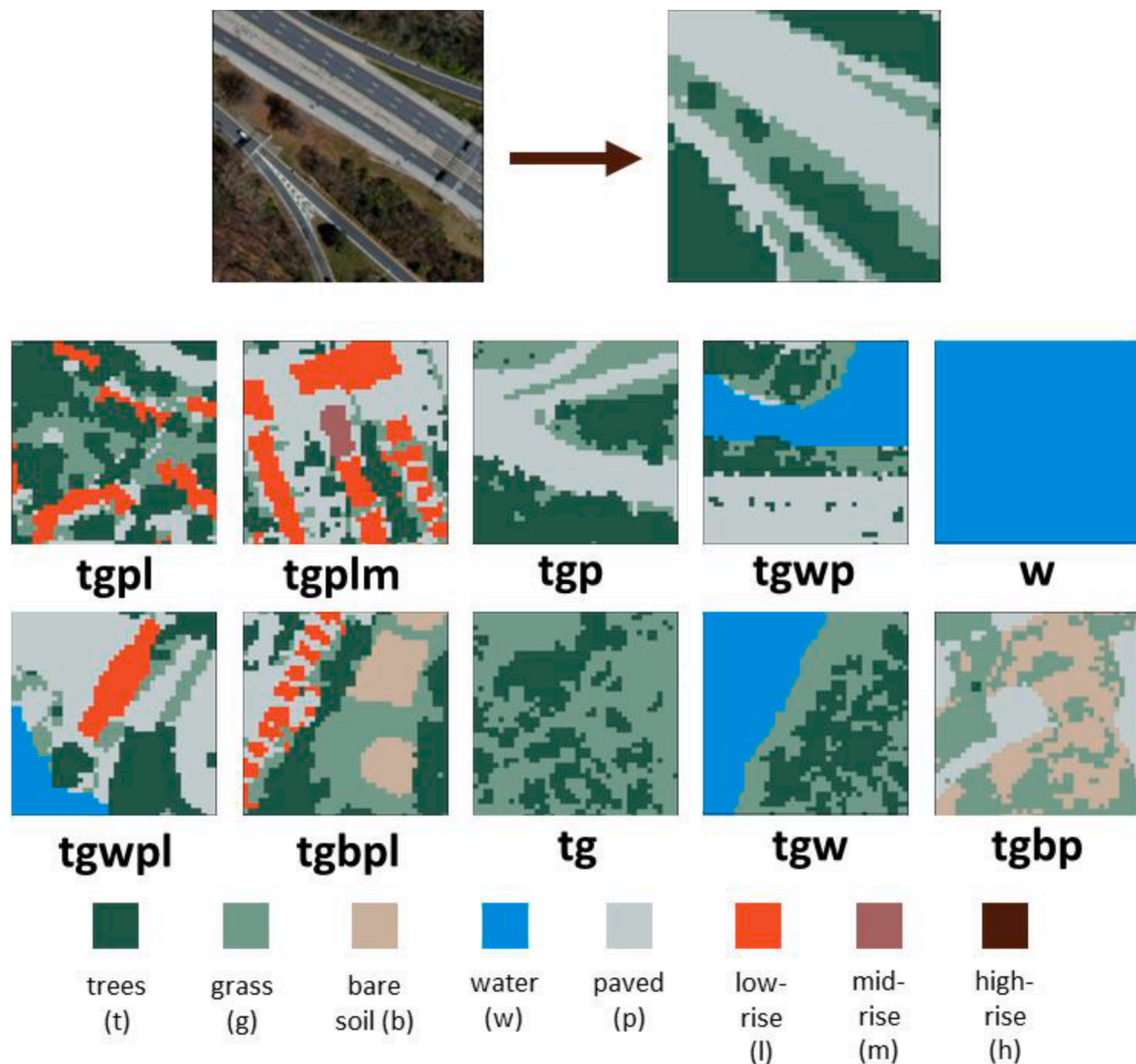


Fig. 2. Examples of pixels of common STURLA classes symbolized on a land cover/building height data raster. Each color within a STURLA cell indicates the presence of a different urban structure component: trees (t), grass (g), bare soil (b), water (w), pavement (p), low-rise buildings (1 – 3 stories) (l), mid-rise buildings (4 – 9 stories) (m), and high-rise buildings (9+ stories) (h).

3. Results

3.1. Variation in landscape structure with $PM_{2.5}$ and BC concentrations among STURLA classes

Differences in both landscape composition and the measured pollutant concentrations they host are evident among the most sampled STURLA classes (Fig. 3). Although a slightly different subset of cells was sampled for $PM_{2.5}$ and BC due to differences in temporal resolutions of sampling equipment (5 s for BC compared to 6 s for $PM_{2.5}$), differences in average STURLA class composition are minimal and did not influence clustering between classes. Daily means for $PM_{2.5}$ among STURLA classes range from $11.47 \pm 1.89 \mu\text{g}/\text{m}^3$ (tgbplm) to $16.60 \pm 4.29 \mu\text{g}/\text{m}^3$ (gpl), while daily means for BC range from $1.25 \pm 0.71 \mu\text{g}/\text{m}^3$ (tgbplm) to $2.31 \pm 1.94 \mu\text{g}/\text{m}^3$ (tgbwp) (Fig. 3). Permutational t-tests reveal that some of the differences in pollutant concentrations between STURLA classes are statistically significant ($p < 0.05$) (Fig. 4). Class gpl demonstrated the most unique $PM_{2.5}$ signature, with daily mean $PM_{2.5}$ concentrations differing significantly from six classes: tgp, tgplm, tgwp, tgbpm, tgbplm, and tgbplh. Class tgbplm presented the most distinct BC signature with the daily average BC concentration being significantly different from four other classes sampled: tgbplh, gpl, tgbwp, and gp.

However, other STURLA classes did not have pollutant concentrations that were significantly different from other classes. More significant differences between classes were found with $PM_{2.5}$ concentrations (17) than with BC concentrations (9) (Fig. 4).

3.2. Spatial modeling of $PM_{2.5}$ and BC

$PM_{2.5}$ predictions by planning district ranged from $12.62 \mu\text{g}/\text{m}^3$ – $13.74 \mu\text{g}/\text{m}^3$; the highest predicted $PM_{2.5}$ concentrations are in the Upper Far Northeast and Lower Far Northeast planning districts, while the lowest predicted concentrations were found in the Central planning district (Table 1). 17 of 18 planning districts underpredicted measured $PM_{2.5}$ concentrations (Predicted $PM_{2.5}$ / Measured $PM_{2.5}$ ratio < 1), which ranged from $12.74 \mu\text{g}/\text{m}^3$ – $14.11 \mu\text{g}/\text{m}^3$ (Table 1). $PM_{2.5}$ modeling was the most accurate in the Lower South district, with a difference of $0.02 \mu\text{g}/\text{m}^3$ between predicted and measured concentrations, but least accurate in the South district, with a $0.38 \mu\text{g}/\text{m}^3$ difference between predicted and measured concentrations. Conversely, the model overpredicted BC concentrations in all 18 planning districts, and generally overpredicted BC concentrations by STURLA class (Table 1). Predicted BC concentrations ranged from $1.54 \mu\text{g}/\text{m}^3$ – $1.78 \mu\text{g}/\text{m}^3$, while measured BC concentrations ranged from $1.49 \mu\text{g}/\text{m}^3$ – $1.66 \mu\text{g}/\text{m}^3$.

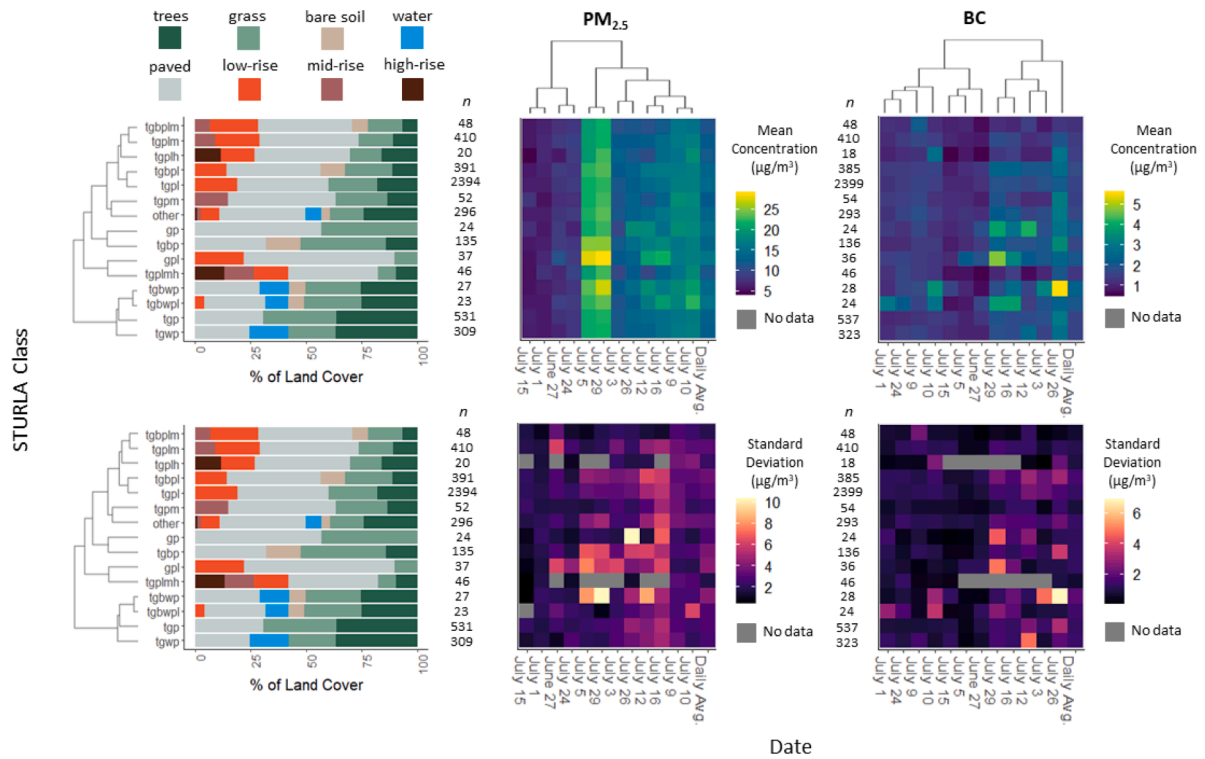


Fig. 3. Composition of the average cell sampled for each class (left), sample sizes, and daily/overall means and standard deviations of measured $PM_{2.5}$ (middle) and BC (right) concentrations. Overall means are represented in the top heatmaps, while standard deviations are represented in the bottom heatmaps; darker colors (blue, purple) represent lower concentrations and lighter colors (yellow) represent higher concentrations. Dendrograms reflect similarities in pollutant concentrations between days (top) and STURLA class composition (left). We encourage the reader to download the figure to zoom into specific small text and data they are interested in viewing. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

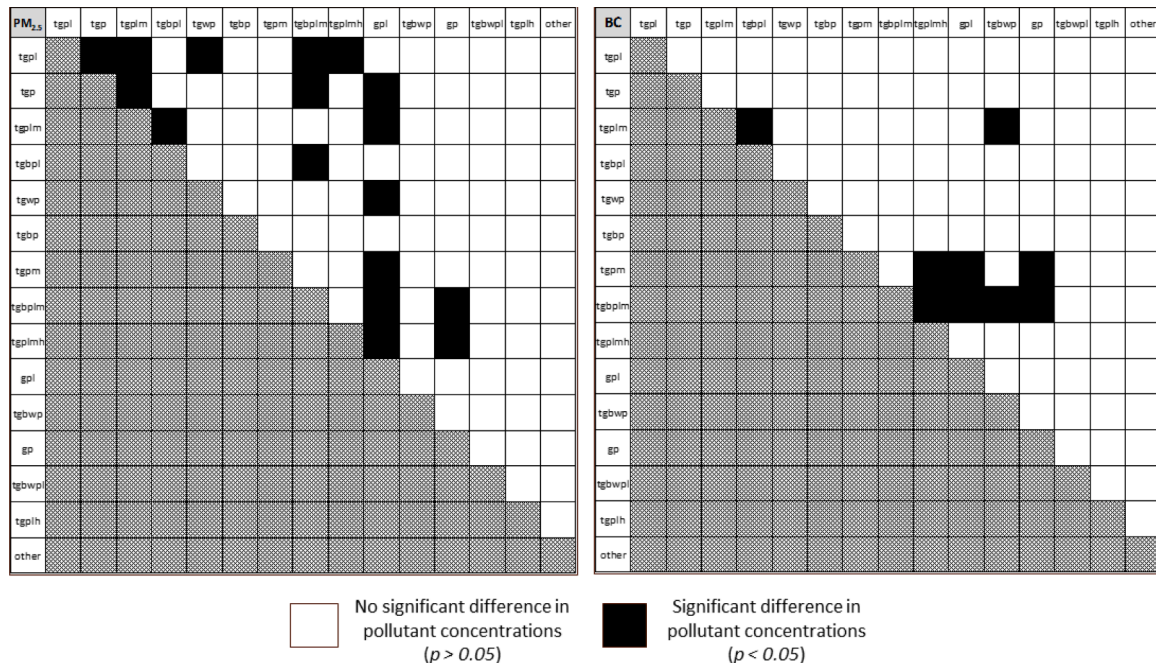


Fig. 4. Results of pairwise permutational t -tests between STURLA classes comparing average daily pollutant concentrations for BC (left) and $PM_{2.5}$ (right). Black cells indicate significant differences in pollutant concentrations between classes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

m^3 . BC predictions are highest in the Lower South district and lowest in the Central district. BC modeling was most effective in the Central, Lower Far Northeast, North, North Delaware, River Wards, and

University Southwest planning districts, all of which have $0.05 \mu g/m^3$ between predicted and measured values; in the Lower South district, the difference between predicted and measured BC concentrations is at its

Table 1

Summary of measured pollutant concentrations, predicted pollutant concentrations, differences between predicted and measured, and validation error by Philadelphia planning district.

Planning District	Mean Predicted PM _{2.5}	Mean Measured PM _{2.5}	P – M (PM _{2.5})	Validation Error	Mean Predicted BC	Mean Measured BC	P – M (BC)	Validation Error
Central	12.62	12.74	−0.12	0.994	1.54	1.49	0.05	1.040
Central Northeast	13.60	13.88	−0.28	0.981	1.65	1.57	0.08	1.062
Lower Far Northeast	13.74	14.11	−0.37	0.975	1.68	1.63	0.05	1.046
Lower North	13.40	13.55	−0.15	0.991	1.62	1.56	0.06	1.040
Lower Northeast	13.71	14.03	−0.32	0.978	1.65	1.59	0.06	1.040
Lower Northwest	13.59	13.83	−0.24	0.984	1.64	1.55	0.09	1.078
Lower South	12.83	12.85	0.02	1.036	1.78	1.66	0.12	1.134
Lower Southwest	13.59	13.84	−0.25	0.988	1.72	1.65	0.07	1.069
North	13.54	13.75	−0.21	0.986	1.64	1.59	0.05	1.036
North Delaware	13.73	14.01	−0.28	0.983	1.70	1.65	0.05	1.038
River Wards	13.63	13.85	−0.22	0.988	1.71	1.66	0.05	1.052
South	13.56	13.94	−0.38	0.975	1.68	1.62	0.06	1.043
University Southwest	13.20	13.38	−0.18	0.989	1.61	1.56	0.05	1.037
Upper Far Northeast	13.74	14.09	−0.35	0.976	1.66	1.60	0.06	1.047
Upper North	13.62	13.95	−0.33	0.976	1.65	1.58	0.07	1.044
Upper Northwest	13.55	13.85	−0.30	0.979	1.64	1.57	0.07	1.049
West	13.58	13.88	−0.30	0.979	1.64	1.57	0.07	1.040
West Park	13.53	13.60	−0.07	0.997	1.67	1.59	0.08	1.057

highest (0.12 $\mu\text{g}/\text{m}^3$).

The importance of each landscape element per STURLA class was used to identify drivers in pollution heterogeneity. Pavement was the most important variable in modeling PM_{2.5}, followed by high-rise, grass, trees, mid-rise, water, and low-rise (Fig. A2). In modeling BC, low-rise was the most important variable, followed by pavement, trees, grass, mid-rise, high-rise, and water (Fig. A2). In both models, bare soil did not contribute to predictions of pollutant concentrations. Predictions varied

by STURLA class (Fig. 5A, B). Philadelphia's most frequent class, *tgpl*, has a mean prediction of 13.71 $\mu\text{g}/\text{m}^3$; modeling overpredicted the average measured concentration of the class by 1.64 $\mu\text{g}/\text{m}^3$. STURLA classes *gbp*, *tgp*, and *gpl* are among the classes with the highest predicted concentrations, while *pm*, *tgwpl*, *gwp* had the lowest (Supplemental Table 1). Variation in PM_{2.5} concentrations across the city were largely explained by differences in sampled STURLA classes ($R^2 = 0.68$, RMSE 1.10 $\mu\text{g}/\text{m}^3$). PM_{2.5} predictions ranged from 8.77 – 15.29 $\mu\text{g}/\text{m}^3$; actual

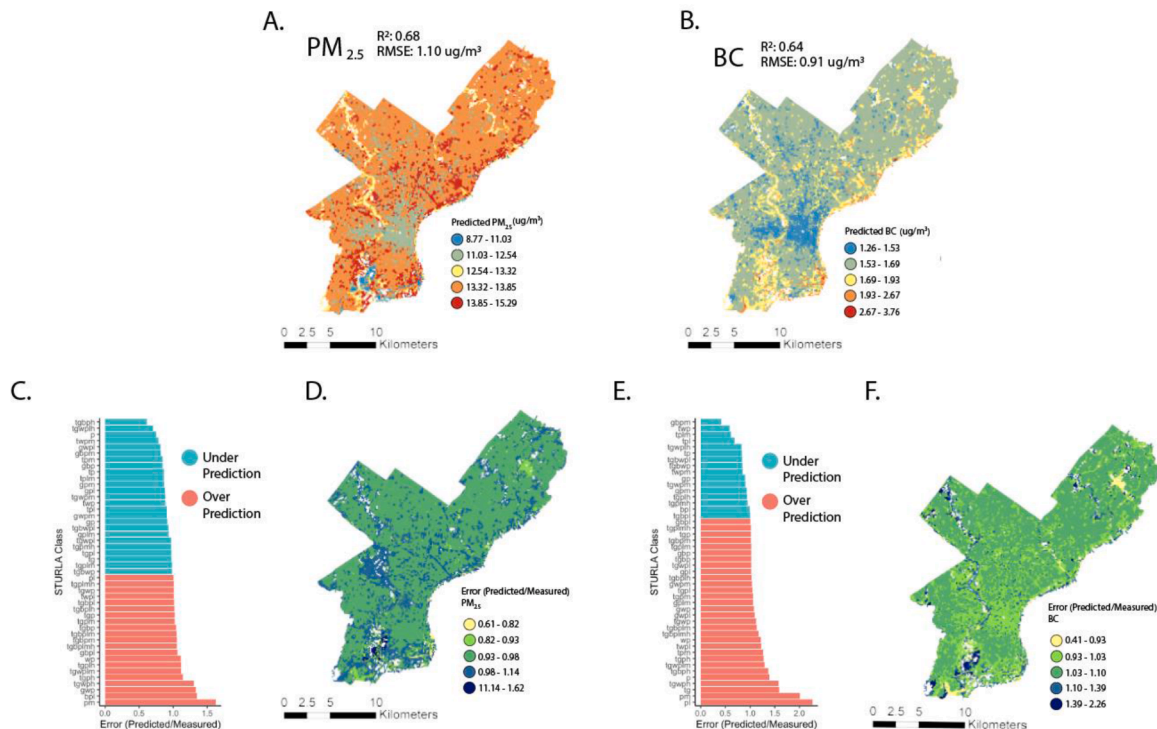


Fig. 5. A. Predicted PM_{2.5} concentrations by quantile. B. Predicted BC concentrations by quantile. C. Barplot of PM_{2.5} model error separated by STURLA class, with bar colors indicating underpredictions (blue) and overpredictions (red). D. Map of PM_{2.5} model validation error throughout Philadelphia. E. Barplot of BC model error separated by STURLA class, with bar colors indicating underpredictions (blue) and overpredictions (red). F. Map of BC model validation error. We encourage the reader to download the figure to zoom into specific small text and data they are interested in viewing. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

PM_{2.5} concentrations by class ranged from 5.40 – 22.21 µg/m³. Differences between STURLA class composition were slightly less effective in explaining variation in BC concentrations ($R^2 = 0.64$, RMSE 0.91 µg/m³). BC predictions by class were generally higher than measured concentrations (Fig. 5E, F), and ranged from 1.26 µg/m³ to 3.76 µg/m³; actual concentrations by class ranged from 0.85 – 5.45 µg/m³. BC predictions in *tgpl* hosted predicted BC values of 1.65 µg/m³ and over-predicted measured BC in *tgpl* pixels by 0.07 µg/m³. Classes with more internal class elements generally have lower predicted air pollution concentrations; *tpl*, *tp*, and *twp* were the classes with the highest BC predictions, while *tgph*, *tgplmh*, and *tgplh* had the lowest.

4. Discussion

4.1. Variation in PM_{2.5} and BC by STURLA class

PM_{2.5} and BC varied by STURLA class (Fig. 3); while some classes, such as *gpl*, had pollutant concentrations that were distinct from multiple classes, no class had PM_{2.5} concentrations or BC concentrations that were significantly different from all commonly sampled classes (Fig. 4). Among the 14 most sampled STURLA classes, we find that the classes containing mid-rise and high-rise buildings hosted lower concentrations of PM_{2.5} and BC relative to other commonly sampled classes; the five classes containing *m* or *h* (*tgplm*, *tgpm*, *tgplh*, *tgplmh*, and *tgplm*) show the lowest average concentrations of PM_{2.5} and BC (Fig. 3). Four of these classes (*tgpm*, *tgplh*, *tgplmh*, and *tgplm*) also host the lowest daily variation in PM_{2.5} concentrations, while all five have the lowest daily variation in BC concentrations (Fig. 3). These results are unique given the presence of taller buildings and comparatively lower proportion of greenspace. While trees and grass are found in these classes, these landscape elements are partially diminished by adding in the elements of the built environment. Air pollution tends to be higher in areas with greater proportions of tall buildings (Aristodemou et al., 2018), while areas with a greater proportion of vegetation tend to have lower concentrations of air pollutants (Leung et al., 2011; Li et al., 2016). The taller buildings present in these classes can adversely impact wind flow and pollutant dispersal, causing an increase in pollutant concentrations closer to the peak of the building while decreasing concentrations at the ground-level where sampling occurred (Aristodemou et al., 2018; Zhang, Qi, Jiang, Zhou, & Wang, 2013). Likewise, potential sources of PM_{2.5} and BC may simply be less abundant and/or smaller in magnitude where these classes are found, despite PM concentrations typically being higher in areas with denser built environment (Zhou & Lin, 2019). It is worth noting that classes with *m* and *h* components were generally sampled less frequently, with the exception of *tgplm*, because they are less prevalent in the city's landscape. Some classes, such as *tgplh* and *tgplmh*, were not sampled enough to be able to quantify variability in pollutant concentrations on some days (Fig. 3). Smaller sample sizes may have been less effective at capturing the full range of pollutant concentrations for specific classes than larger sample sizes.

While classes such as *tgplm*, *tgplm*, and *tgplh*, are compositionally similar and have similar concentrations of PM_{2.5} and BC (Fig. 3), others display pronounced differences in pollutant levels despite compositional similarities with other STURLA classes. Among the most commonly sampled STURLA classes, *gpl* hosted the highest PM_{2.5} concentrations and the third-highest BC concentrations. Class *gpl* is largely dominated by built environment, with roughly 89.9% of the *gpl* class characterized by pavement and low-rise buildings. In class *tgplmh*, the class most similar to *gpl* by STURLA elements, we observe the second-lowest daily average PM_{2.5} and BC concentrations throughout the sampling period. Conversely, class *gp* – also compositionally similar to *gpl* – hosted relatively high concentrations of PM_{2.5} and BC just like *gpl*. In this class, we observe the third-highest daily average PM_{2.5} concentration and second-highest daily average BC concentration. The differences in these classes may be explained by the differences in variety of urban landscape components present; *gp* and *gpl* classes lack the trees, mid-rise, and high-

rise buildings that are present in the *tgplmh* class. Even though *gp* is considerably more vegetated than *tgplmh* (43.2% grass in *gp* vs. 17.8% trees/grass in *tgplmh*), class *gp* has pollutant concentrations that are closer to *gpl*, a class with 89.8% built environment. The high pollutant concentrations in *gp* and *gpl* suggest that grass does not facilitate a meaningful decrease in PM in urban environments, or at least in areas of the urban environment that consist mostly of built environment. Trees may be more effective at attenuating air pollution than grass; most classes containing trees, with the exception of *tgplmh*, have lower concentrations of PM_{2.5} and BC than *gp* and *gpl*. However, given the prevalence of classes with trees in Philadelphia, it is unclear whether it is the abundance of trees or the lack of built environment that contributes more to lower pollutant concentrations in these classes.

4.2. Spatial prediction of air pollution

STURLA was able to accurately model two types of air pollution across the city with low error. The proportion of STURLA components present in a pixel, can be used to predict PM pollutant concentrations despite heterogeneity in sources of PM and BC, sampling efforts (e.g. on highways, near parks, stalled in traffic), and daily variation (Fig. 3). Modeling was generally accurate for both PM_{2.5} and BC; the largest difference between predicted and measured concentrations was 0.38 µg/m³ for PM_{2.5} and 0.12 µg/m³ for BC. These results support the idea that differences in three-dimensional urban structure alter the presence, abundance, and distribution of air pollution. Likewise, they suggest that STURLA can be used as an environmentally meaningful unit for urban planning with regard to air pollution.

STURLA relied on the built environment to predict pollutant concentrations as seen in other modeling studies of urban air pollution distributions (Ross et al., 2007; Weichenthal et al., 2016). Pavement and high-rise were the most important STURLA components in modeling PM_{2.5}, while low-rise and pavement were the most important components in modeling BC (Fig. A2). Pavement's importance in modeling the relationships between STURLA and PM is likely a function of the sampling design, which requires driving on roads throughout the sampling period, as well as the prevalence of pavement throughout Philadelphia. Vehicle emissions are a major contributor to PM emissions on roads (Cheng & Li, 2010), and developed areas in the urban environment are often in close proximity to facilities that generate PM pollution. The importance of low-rise buildings in BC modeling and of high-rise buildings in PM_{2.5} underscore the potential for buildings to influence pollutant concentrations. These buildings are not only associated with PM_{2.5} and BC pollution, but their structure and organization throughout the urban environment can also influence local pollutant concentrations. This may be due to physically blocking the dispersal of particles in the air. Trees and grass are also relatively important in predicting pollutant concentrations, though not as important as the built components of the environment. Similar to components of the built environment, this may be a result of the sampling design; in our predictions, greenspace is likely less important in part because unable to directly sample in areas without pavement. This also become apparent when model error is mapped where greenspace, such as Fairmount Park, are difficult to accurately predict. As measuring directly in greenspace without pavement was not possible by car, we may underestimate the contribution of trees and grass to air pollution attenuation (Nowak et al., 2006).

Urban structure patterns contributed slightly less explanatory power for BC predictions as they did for PM_{2.5} predictions; the relationship between urban structure and PM_{2.5} has an $R^2 = 0.68$, while the relationship between urban structure and BC has an $R^2 = 0.64$. The weaker correlation between BC and urban structure may be explained at least in part by the fact that BC is only a subset of PM_{2.5}; PM_{2.5} is inherently more abundant in the environment, as it has a greater variety of sources including vegetation, secondary aerosol formation from vehicular emissions (e.g. NO_x and SO_x) (Juda-Rezler et al., 2020), and suspension

of crustal materials such as dust and soil (Querol et al., 2001). BC, in contrast, only comes from anthropogenic sources, and concentrations are largely influenced by road transport (Diaz Resquin et al., 2018). As a result, BC has a slightly weaker overall correlation to urban structure at large.

4.3. Limitations

Though the sampling routes capture a sample of Philadelphia that is representative of the urban structure patterns prevalent in the city, the urban landscape can look quite different in other cities. As a result, some STURLA classes that are present or even abundant in other urban environments are not considered in these analyses. One such example is STURLA class *w*; though it is the sixth most common STURLA class in Philadelphia, we are unable to sample this class as it is impossible to drive through a cell containing only water. The accuracy of the prediction cannot be compared to measured values, as there are none; similar studies in the future should make appropriate adjustments to the experimental design to capture common classes that are otherwise inaccessible (i.e. classes without pavement). Though we include predictions and measurements for all classes with 2+ observations, we do not test for significant differences between classes with fewer than 20 unique sampled cells, nor do we examine how the compositions of these classes influence pollutant concentrations. Infrequently sampled classes constitute a small fraction of the urban structure patterns present throughout Philadelphia, and in the absence of further sampling, it is difficult to accurately predict and characterize pollutant levels in these areas.

Both our PM_{2.5} measurements and predicted values in the STURLA cells where five US EPA PM_{2.5} monitoring sites are located were higher than the US EPA's 24-hour averages at these sites. All the mobile measurements were taken on roads and mobile measurements averages were computed from measurements while driving near EPA's sites. EPA's sites are usually farther from the roads and the inlets of the measurements are at higher level than the inlet during our mobile measurement. Despite these differences and limitations of comparisons, we conclude that mobile measurements may be higher than the US EPA's PM_{2.5} measurements but capture similar patterns.

While meteorological conditions such as wind speed and wind direction can influence air pollutant concentrations, it is difficult to quantify these variables due to the variable speed and direction of the vehicle; as such, while we tried to sample on days with similar weather conditions, we do not include these variables in our analysis. Variation in weather conditions throughout the day, along with traffic, can influence pollutant concentrations as urban structure patterns do. However, a drawback in the mobile monitoring method is that it is difficult to discern between variation caused by spatial and temporal phenomena. Future studies can clarify the precise impacts of urban structure on air pollutant concentrations by adjusting the experimental design to sample at different times of day and focusing specifically on variables that are particularly dependent on temporal changes. Additionally, the use of STURLA is limited by the availability of up-to-date land cover and building height data; as the STURLA profile is based on data from 2017, it may not reflect changes in the Philadelphia's urban landscape that have occurred since then. Increased availability and accuracy of spatial data would make STURLA more effective in real time and would enable more accurate predictions.

5. Conclusions

In this study, we explore the potential of STURLA as a way to simplify and meaningfully describe three-dimensional urban structure in the context of air pollution. Specifically, we sought to determine how variation of particulate matter concentrations could be characterized by composite landcover units. The class *tgblpm* was found to host the lowest PM_{2.5} and BC concentrations, while *gpl* had the highest PM_{2.5}

concentrations ($16.60 \pm 4.29 \mu\text{g}/\text{m}^3$). Class *tgblwp* had the highest BC concentrations ($2.31 \pm 1.94 \mu\text{g}/\text{m}^3$). We find that some classes, such as *gpl* and *tgblpm* have average pollutant concentrations that stand out relative to other classes, and we find that classes generally have more significant differences in PM_{2.5} concentrations than in BC concentrations. We also find that the components of STURLA and the proportions in which they are present are useful in predicting PM_{2.5} and BC concentrations in different STURLA classes throughout the urban landscape. Of the STURLA components, components of the built environment (pavement, low-rise, high-rise) are the strongest predictors of urban PM_{2.5} and BC pollution; low-rise buildings are more important in modeling BC than PM_{2.5}, while the opposite is true for high-rise buildings. Vegetation components of the environment, such as trees and grass, have a fair amount of predictive power regarding PM_{2.5} concentrations as well. The ability to approximate PM_{2.5} concentrations using proportions of STURLA components suggests that careful consideration of urban structure patterns in planning can help cities to plan future development in a way that reduces potential exposure to air pollutants. STURLA may also be helpful in modeling relationships between urban structure and other prominent urban air pollutants of concern, such as ozone (O₃), nitrogen oxides (NO_x) and sulfur oxides (SO_x). Further exploration of STURLA in the context of these other common urban air pollutants may reveal distinct differences between pollutant concentrations among STURLA classes that are not evident when looking solely at PM_{2.5} and BC.

CRedit authorship contribution statement

Lucas E. Cummings: Formal analysis, Writing – original draft. **Justin D. Stewart:** Data curation, Formal analysis, Writing – original draft. **Peleg Kremer:** Conceptualization, Data curation, Writing – original draft, Supervision, Funding acquisition. **Kabindra.M. Shaky:** Conceptualization, Data curation, Writing – original draft, Supervision, Funding acquisition.

Declaration of Competing Interest

None.

Acknowledgments

We would like to thank Meghan Conway, Radley Reist, and Alexander Saad for their assistance in data collection. We would also like to thank Stephen Strader for his help in reviewing this manuscript. Financial support for this study was provided through National Science Foundation (NSF) grant #1832407.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.scs.2021.103510](https://doi.org/10.1016/j.scs.2021.103510).

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