Associations between the Structure of Urban Landscape and Particulate Matter: A STURLA Case Study in Philadelphia, PA

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Declaration of Interest

The authors declare that there is no conflict of interest.

Abstract:

Understanding the relationships between land cover/urban structure patterns and air pollutants is key to sustainable urban planning and development. 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, while $PM_{2.5}$ and BC vary by STURLA class, many of the differences in pollutant concentrations between classes are not significant. However, we also find that the proportions in which STURLA components are present throughout the urban landscape can be used to predict urban air pollution. Among frequently sampled STURLA classes, *gpl* hosted the highest $PM_{2.5}$ concentrations on average (16.60 ± 4.29 μg/m^3), while *tgbwp* hosted the highest BC concentrations (2.31 ± 1.94 μg/m^3). Furthermore, STURLA combined with machine learning modeling was able to correlate $PM_{2.5}$ (R^2= 0.68, RMSE 2.82 μg/m^3) and BC (R^2 = 0.64, RMSE 0.75 μg/m^3) concentrations with the urban landscape and spatially interpolate concentrations where sampling did not take place. These results demonstrate the efficacy of the STURLA methodology in modeling relationships between air pollution and land cover/urban structure patterns.

1.0 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 (UN DESA, 2018). As urban areas expand, a larger proportion of the global population will be exposed to increasingly high and potentially harmful levels of air pollution. At present, 9 out of 10 people regularly breathe air containing unsafe level of air pollutants (WHO, 2018), and approximately 3.7 million premature deaths worldwide can be attributed to elevated air pollutant concentrations each year (Cohen et al., 2017). Elevated levels of air pollutants disproportionately impact people based on race, (Perlin et al. 1999; Perlin et al. 2001; Gray et al. 2013), gender and sexual orientation (Collins et al., 2017) and socioeconomic status (Perlin et al. 1999; Zhou et al. 2011; Gray et al. 2013). To ensure that air quality management is equitable and protects the health of urban populations, it is crucial that we understand how air pollutants interact with the urban environment.

Particulate matter (PM) has been linked to negative health outcomes, including asthma (Halonen et al., 2008; Anenberg et al. 2018), lung cancer (Hamra et al. 2014; Pope et al. 2002), DNA alteration (Sorensen et al. 2003; Shi et al., 2019; Baccarelli et al., 2009), and disrupted immune function (Zelikoff et al., 2008; Honda et al. 2017). Polluted airs also host potentially pathogenic bacteria (Stewart et al., 2020; Liu et al., 2018) and viruses (Wu et al., 2020; Zhu et al., 2020) that may cause disease and aggravate pre-existing conditions. Fine particulate matter ($PM_{2.5}$) is of significant concern due to its abundance in urban atmospheres, and subsequent potential to cause respiratory and cardiovascular damage (Dockery et al., 1993; Paul et al., 2019; Rabinovitch et al., 2006; Shakya et al., 2016). Black carbon (BC), a subset of $PM_{2.5}$, is generated through incomplete combustion of fossil fuels and is particularly prevalent in urban areas. Unlike $PM_{2.5,}$ almost all of BC originates from anthropogenic sources, with biomass fires being the only natural source of BC (Hitzenberger & 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 land cover, urban structure, and ambient air pollution (Eeftens et al. 2012; Yuan et al. 2019). In urban areas such as Philadelphia, particulate matter concentrations vary across neighborhoods as a result of 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 local pollutant dispersal (Baldauf et al., 2016; Gallagher et al., 2015; Ng & Chau, 2013; Yang et al., 2020). Though many urban areas are characterized by dense built environment, different types of urban green space (e.g. urban forest, parks, gardens, and private yards) are an integral part of the urban landscape. Over the last few decades, cities are increasingly adopting strategies such as urban greening to counteract environmental degradation and enhance human wellbeing. However, these strategies and their efficacy in mitigating urban air pollution are still unclear (Nemitz et al., 2020). While vegetation such as trees and grasses have been shown to reduce air pollution by facilitating pollutant deposition and uptake of particulate matter, they are also capable of causing an increase in local pollutant concentrations through biogenic emissions that serve to 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).

Although it is becoming increasingly clear how individual components of urban environments influence air pollution, complex urban topologies make it difficult to understand how these individual components interact to influence air pollution at more localized scales. In urban environments, land cover and urban structures often change drastically over short distances (Cadenasso et al., 2007). While cities may contain common environmental features such as water and greenspace, 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, sustainable development is contingent on reproducible and scalable analyses that geographically meaningful units for urban planning and development. To this end, there have been efforts to streamline the characterization of cities at smaller scales. The Structure of Urban Landscape (STURLA) composite classification allows for modeling of three-dimensional urban areas at fine spatial scales. STURLA does so by using fine-scale land cover and building height data to identify common compositions of urban environments (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., 2021), as well as the phylogenetic diversity of the atmospheric microbiome (Stewart et al. 2021). STURLA allows for meaningful classifications of urban structure and land cover, which 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;

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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 ($PM_{2.5}$) and black carbon (BC) throughout the city of Philadelphia over the course of 12 days during the summer of 2019 (Cummings & Stewart et al., 2021, preprint). We use STURLA (Hamstead et al., 2016) in conjunction with the collected air pollution data to analyze the urban structure-air pollution relationship across the city of Philadelphia.

2.0 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 1,584,138 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 (Figure 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 (Figure 1). A fishnet with 120m^2 pixels was overlaid on the joined land cover / building height raster. STURLA classifications for each cell were determined based on the presence of each land cover / 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*, *tgp*, *tgbpl*, *tgwp*, and *w* (Figure 1). Letters in the STURLA class code denote the presence of specific features of the urban landscape (Figure 2).

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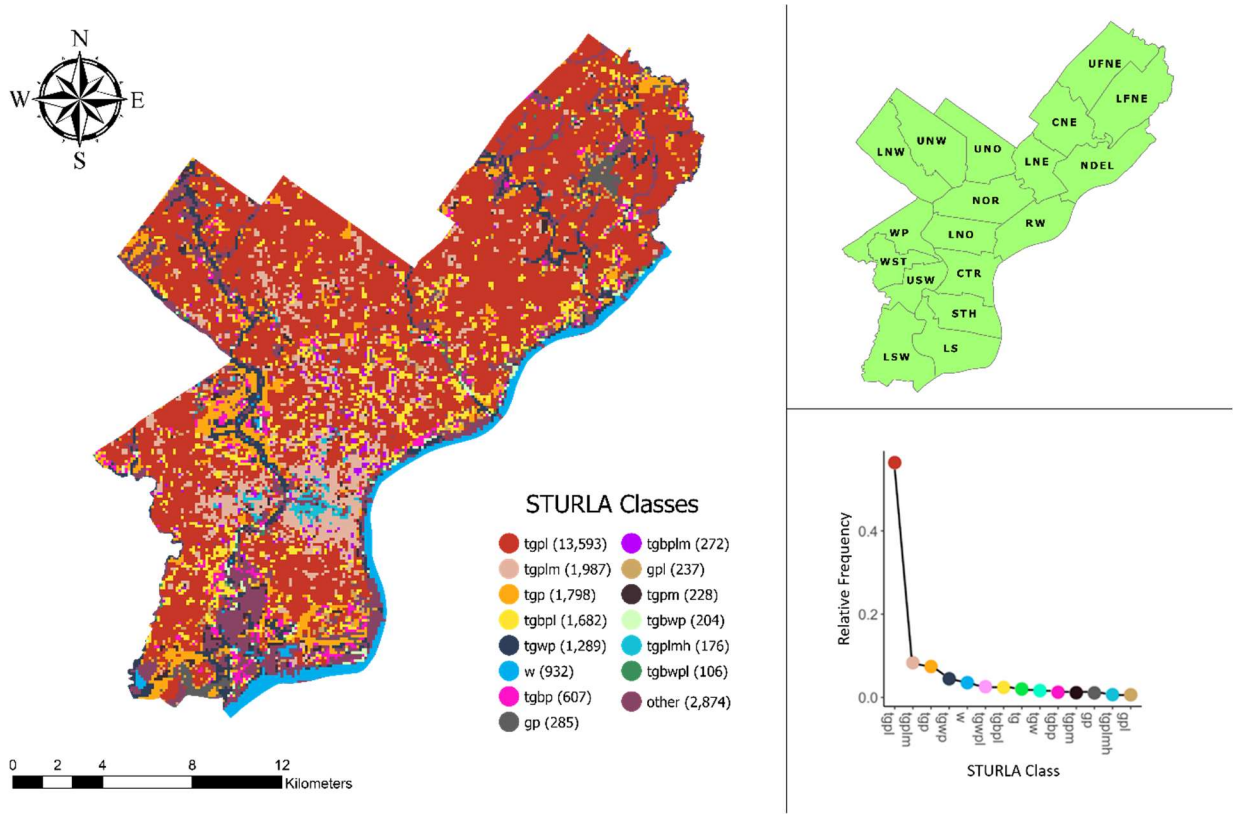

Figure 1. Map of STURLA classes in Philadelphia, Pennsylvania (left). Classes symbolized include the 14 most sampled classes, which make up 85.5% of Philadelphia; *w* is also included for representation of major waterways. The "other" class consists of the other 72 classes found throughout Philadelphia 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.

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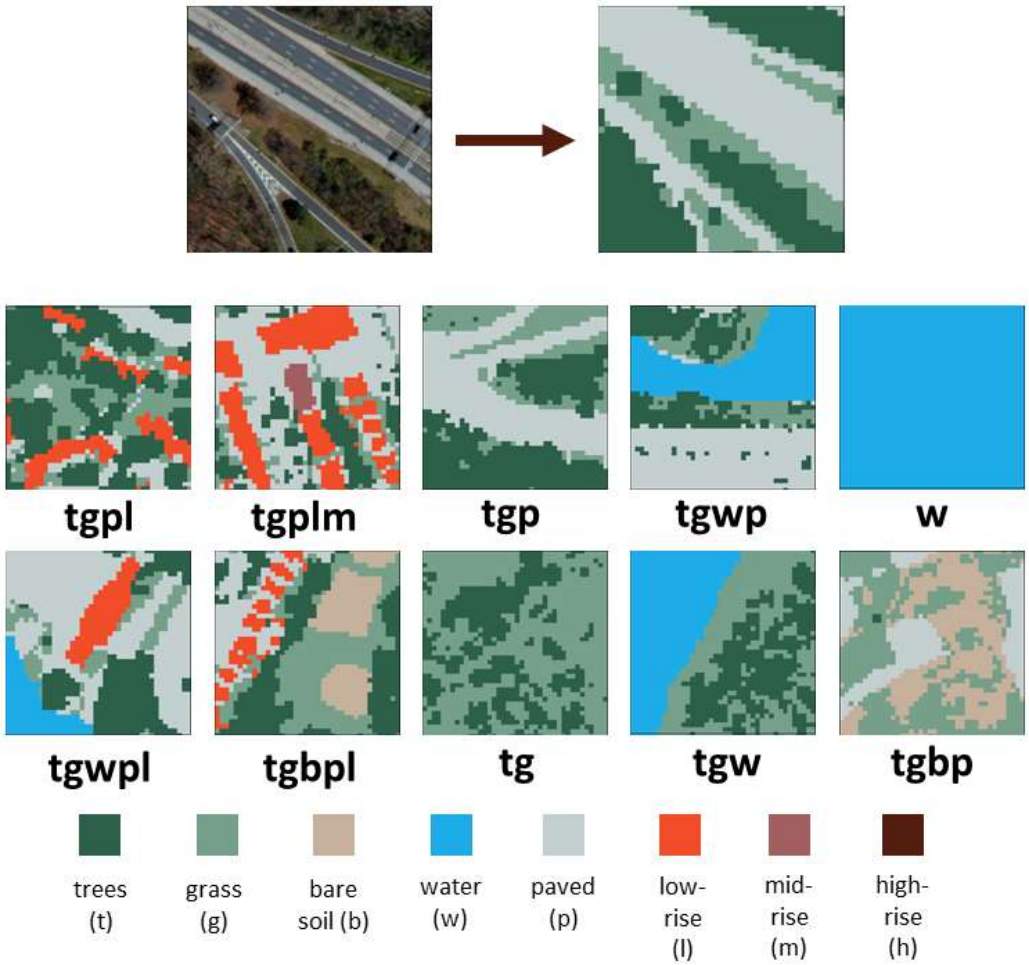

Figure 2. Examples of pixels of common STURLA classes symbolized on a land cover/building height data raster. Each color within a STURLA cell indicates the presence of a different urban structure component: trees (*t*), grass (*g*), bare soil (*b*), water (*w*), pavement (*p*), low-rise buildings (1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

2.3 *Sampling Description*

$PM_{2.5}$ 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), $PM_{2.5}$ 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 & Stewart et al. 2021 (preprint). 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 (Figure A1). 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, 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. Sampling occurred on days where inclement weather (i.e. rain) did not pose a risk to the monitoring equipment; as such, weather conditions during the sampling days were similar (Table A3). Sampling began between 6 – 7 AM on one of the two routes and continued until the entirety of the route was traveled; the sampling period on any given day ranged from about 8 hours to 10.5 hours. Vehicle speed averaged ~20 km/hr throughout the data collection period.

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 land cover / 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 (Figure 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.

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, 2012). Using the "*caret"* package (Kuhn et al. 2008) in R (3.3.6) (Ihaka &

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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 land cover / 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. We define validation error as the ratio of predicted to measured concentrations. 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. Model predictions and results were joined by STURLA class and visualized using ArcMap 10.7.1.

3.0 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 (Figure 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 seconds for BC compared to 6 seconds 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 $\mu g/m^3$ (*tgbplm*) to 16.60 $\pm$ 4.29 $\mu g/m^3$ $\mu g/m^3$ (*gpl*), while daily means for BC range from 1.25 $\pm$ 0.71 $\mu g/m^3$ (*tgbplm*) to 2.31 $\pm$ 1.94 $\mu g/m^3$ (*tgbwp*) (Figure 3). Permutational t-tests reveal that some of the differences in pollutant concentrations between STURLA classes are statistically significant ($p < 0.05$) (Figure 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, tgpm, tgbplm,* and *tgplmh*. Class *tgbplm* presented the most distinct BC signature with the daily average BC concentration being significantly different from four other classes sampled: *tgplmh, 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) (Figure 4).

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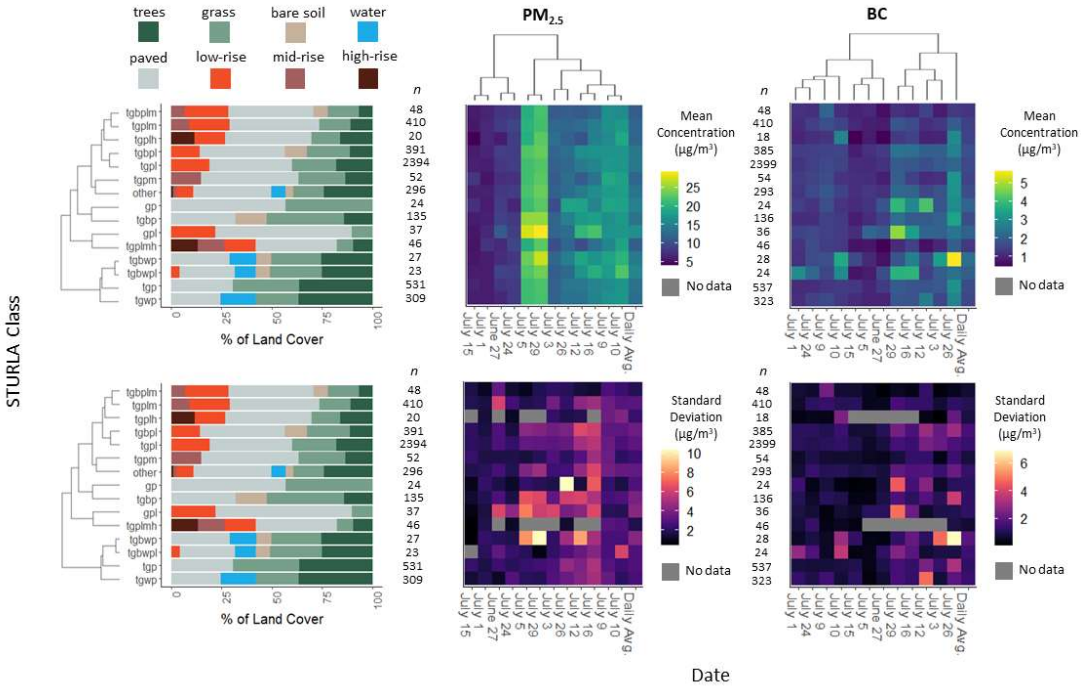

Figure 3. Composition of the average cell sampled for each class (left), sample sizes, and daily/overall means and standard deviations of measured $PM_{2.5}$ (middle) and BC (right) concentrations. Overall means are represented in the top heatmaps, while standard deviations are represented in the bottom 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).

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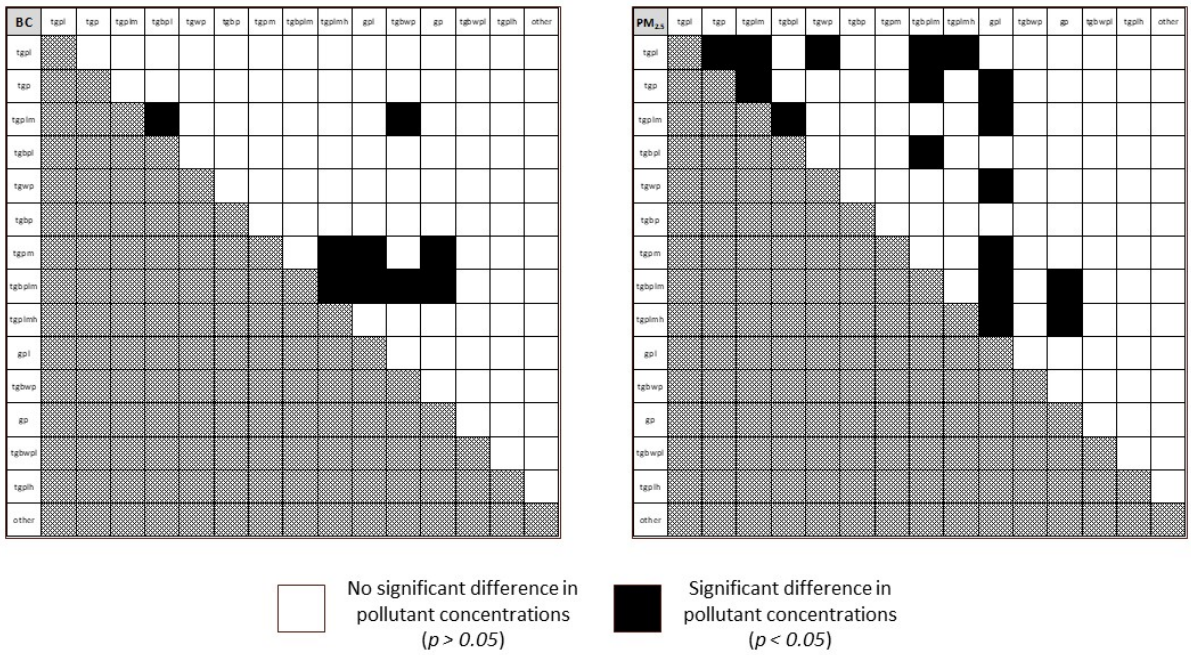

Figure 4. Results of pairwise permutational t-tests between STURLA classes comparing average daily pollutant concentrations for BC (left) and $PM_{2.5}$ (right). Black cells indicate significant differences in pollutant concentrations between classes.

3.2 *Spatial Modeling of $PM_{2.5}$ and BC*

Pavement was the most important variable in modeling $PM_{2.5}$, followed by high-rise, grass, trees, mid-rise, water, and low-rise (Figure 5A). In modeling BC, low-rise was the most important variable, followed by pavement, trees, grass, mid-rise, high-rise, and water (Figure 5E). In both models, bare soil did not contribute to predictions of pollutant concentrations (Figure 5A, 5E). Predictions varied by STURLA class (Figure 5B, 5F). Philadelphia's most frequent class, *tgpl*, has a mean prediction of 13.71 $\mu g/m^3$; modeling overpredicted the average measured concentration of the class by 1.64 $\mu g/m^3$. 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 $\mu g/m^3$). $PM_{2.5}$ predictions ranged from 8.77 – 15.29 $\mu g/m^3$; actual $PM_{2.5}$ concentrations by class ranged from 5.40 – 22.21 $\mu g/m^3$. Differences between STURLA class composition were slightly less effective in explaining variation in BC concentrations ($R^2 = 0.64$, RMSE 0.91 $\mu g/m^3$). BC predictions by class were generally higher than measured concentrations (Figure 5G), and ranged from 1.26 $\mu g/m^3$ to 3.76 $\mu g/m^3$ (Figure 5F); actual concentrations by class ranged from 0.85 – 5.45 $\mu g/m^3$. BC predictions in *tgpl* hosted predicted BC values of 1.65 $\mu g/m^3$ and overpredicted measured BC in *tgpl* pixels by 0.07 $\mu g/m^3$. Classes *tpl, tp,* and *twpm* were the classes with the highest BC predictions, while *tgbph, tgplmh,* and *tgbplh* had the lowest predictions (Figure 5G).

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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

$PM_{2.5}$ predictions by planning district ranged from 12.62 μg/m^3 – 13.74 μg/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 μg/m^3 – 14.11 μg/m^3 (Table 1). $PM_{2.5}$ modeling was the most accurate in the Lower South district, with a difference of 0.02 μg/m^3 between predicted and measured concentrations, but least accurate in the South district, with a 0.38 μg/m^3 difference between predicted and measured concentrations. Conversely, the model overpredicted BC concentrations in all 18 planning districts, and generally overpredicted BC

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concentrations by STURLA class (Table 1, Figure 5G). Predicted BC concentrations ranged from 1.54 μg/m^3 – 1.78 μg/m^3, while measured BC concentrations ranged from 1.49 μg/m^3 – 1.66 μg/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 μg/m^3 between predicted and measured values; in the Lower South district, the difference between predicted and measured BC concentrations is at its highest (0.12 μg/m^3).

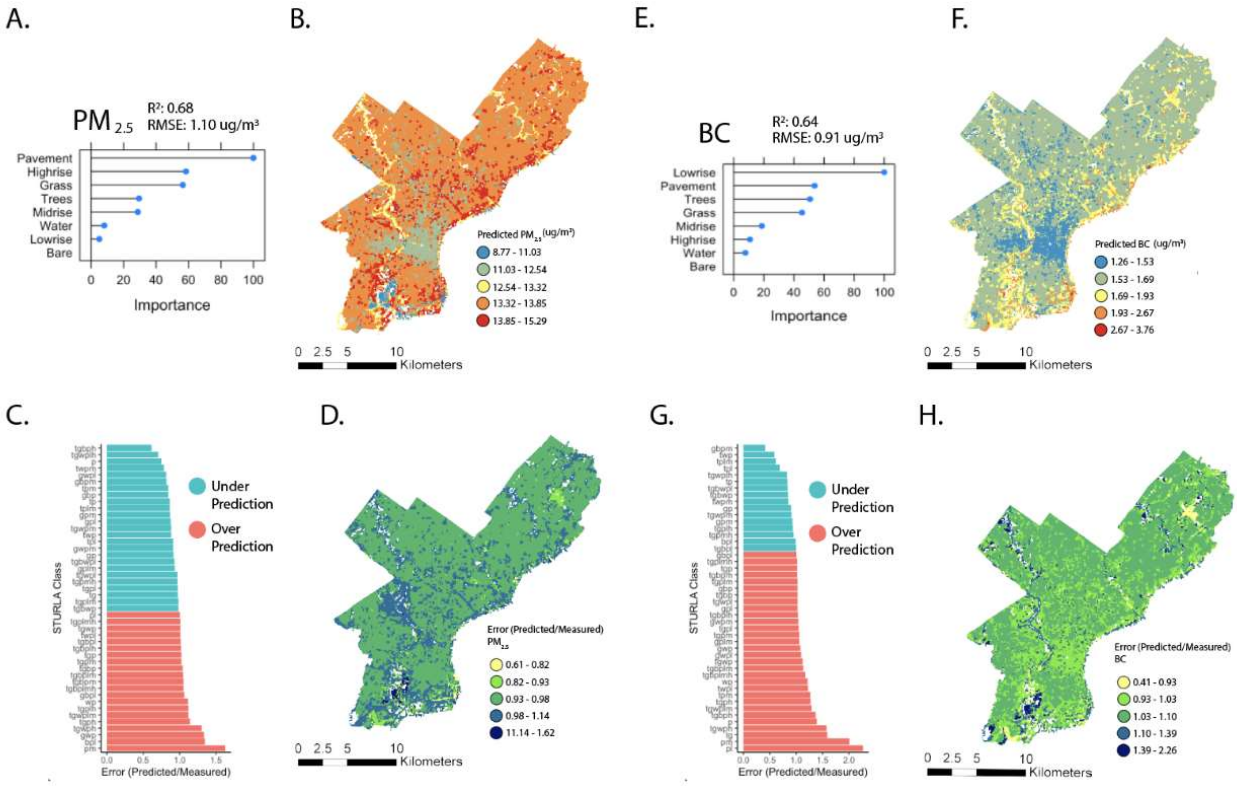

Figure 5. A. $PM_{2.5}$ Random Forest Regression variable importance, correlation coefficient (R^2) and error (RMSE). B. Predicted $PM_{2.5}$ concentrations by quantile. C. Barplot of $PM_{2.5}$ model error separated by STURLA class, with bar colors indicating underpredictions (blue) and overpredictions (red). D. Map of $PM_{2.5}$ model validation error throughout Philadelphia. E. BC Random Forest Regression variable importance, correlation coefficient (R^2) and error (RMSE). F. Predicted BC concentrations by quantile. G. Barplot of BC model error separated by STURLA class, with bar colors indicating underpredictions (blue) and overpredictions (red). H. Map of BC model validation error.

4.0 Discussion

4.1 *Variation in $PM_{2.5}$ and BC by STURLA Class*

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$PM_{2.5}$ and BC varied by STURLA class (Figure 3), though most of the differences between classes are not statistically significant; no class had $PM_{2.5}$ concentrations or BC concentrations that were significantly different from all commonly sampled classes (Figure 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 *tgbplm*) show the lowest average concentrations of $PM_{2.5}$ and BC (Figure 3). Four of these five classes (*tgpm, tgplh, tgplmh,* and *tgbplm*) also have the lowest daily variation in $PM_{2.5}$ concentrations, while all five have the lowest daily variation in BC concentrations (Figure 3). These results are unusual given the presence of taller buildings and relative lack of the natural environment; air pollutant concentrations tend to be higher in areas with a greater proportion of taller 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 & Chu, 2013). Likewise, potential sources of PM 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, except for *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 (Figure 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 *tgbplm, tgplm,* and *tgplh,* are compositionally similar and have similar concentrations of $PM_{2.5}$ and BC (Figure 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 *gpl* land cover characterized by pavement and low-rise buildings (Figure 3). 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

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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 *tgbwpl,* 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*

As the most sampled STURLA classes generally do not have significantly different $PM_{2.5}$ and BC concentrations from other common classes (Figure 4), it is difficult to predict specific urban structure given just $PM_{2.5}$ and BC concentrations. However, the details of within class composition, or the proportion of STURLA components present in a given grid cell, can be used to predict PM pollutant concentrations despite heterogeneity in sources of PM and BC and sampling (e.g. on highways, near parks, stalled in traffic) and daily variation (Figure 3). Modeling was generally accurate for both $PM_{2.5}$ and BC; the largest difference between predicted and measured concentrations was 0.38 $\mu g/m^3$ for $PM_{2.5}$ and 0.12 $\mu g/m^3$ for BC (Table 1). Both models relied heavily on built environment to predict pollutant concentrations; 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 (Figure 5A, 5E). 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. Vehicular 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 the importance of high-rise buildings in $PM_{2.5}$ monitoring underscore the potential for buildings to influence pollutant concentrations; these buildings are not only positively associated with $PM_{2.5}$ and BC pollution, but their structure and organization throughout the urban environment can also influence local pollutant concentrations. Trees and grass are also relatively important in predicting pollutant concentrations, though not as important as the built components of the environment (Figure 5A, 5E). Trees and grass may be less important to the modeling due to their relative absence in urban environments, or because their presence in urban environments simply does not exert as strong an influence on pollutant concentrations.

Urban structure patterns did not contribute as much 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 $R^2 = 0.64$ (Figure 5). The lower 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 (Resquin et al., 2018). As a

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result, BC has a slightly lower overall correlation to urban structure at large. These results suggest that sustainable urban planning focused on limiting exposure to air pollutants should focus on limiting built environment in favor of open spaces and natural environment to reduce potential sources of PM pollution, reduce variability in pollutant concentrations, and increase the capability of the urban environment to control pollutant levels. Vegetation specifically has been found to be instrumental in reducing PM concentrations (Escobedo & Nowak, 2009; Yin et al., 2011).

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 fraction of the land cover/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. 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.

5.0 Conclusions

In this study, we explore the potential of STURLA as a way to simplify and meaningfully describe land cover and three-dimensional urban structure in the context of PM. Specifically, we sought to determine whether or not differences in particulate matter concentrations could be characterized by unique STURLA classifications, and explore the ability for different elements of land cover/urban structure to be used as predictors of PM concentrations. The class *tgbplm* was found to have the lowest $PM_{2.5}$ and BC concentrations, while *gpl* had the highest $PM_{2.5}$ concentrations (16.60 ± 4.29 $\mu g/m^3$) and *tgbwp* had the highest BC concentrations (2.31 ± 1.94 $\mu g/m^3$). While classes such as *gpl* and *tgbplm* had pollutant concentrations that stood out relative to other classes, we generally find a lack of significant differences between pollutant concentrations among classes, making it difficult to characterize urban structure

patterns based solely on concentrations of $PM_{2.5}$ and BC. However, we found 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 land cover and 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 (O_3), 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.

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