International Journal of Geospatial and Environmental Research

Volume 7 | Number 1 Article 3

March 2020

A Pilot Study on the Relationship between Urban Green Spaces and Fine Particulate Matter

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Abstract

This study aims at identifying the relationships among various variables that influence city-wide $PM_{2.5}$ pollution levels in the six largest cities in Texas. The variables were categorized into three groups for statistical analysis: 1) urban components (city land area, urban population, population density); 2) green space components (coverage, percentage, connectivity, and shape); and 3) meteorological factors (ambient temperature and wind speed). To identify the relationship between meteorological features and daily $PM_{2.5}$ concentration, we used descriptive statistics for each city and all six cities combined. A bivariate statistical test was used to examine the correlation between urban and green feature components and city-level $PM_{2.5}$. To avoid a collinearity problem, the combination of variables that have perfect correlation (e.g., city land area and population) were excluded from the statistical model. Lastly, the hierarchical linear modeling (HLM) technique was used to estimate the effects of the meteorological features and urban and green space variables on the daily particle pollution level, which accounts for the clustering of particulate measurements within cities. The results showed that city-wide particulate pollution has significant, positive associations with temperature, city land area, population, population density, and shape complexity, and negative associations with wind speed, amount of green spaces, tree canopy, and connectivity of green spaces. It is notable that there are negative synergies in the cities with higher population density where there was a greater increase in the pollution level. Similarly, the cities with less green spaces exhibited a modest green space mitigation effect, whereas the cities with more green spaces had only a gradual increase in the pollution level even if it increased due to a higher temperature. This study indicates that both the quantity and spatial configuration of green spaces can play an important role in managing fine particulate matter in large cities.

Keywords

Urban Green Spaces, Fine Particulate Matter, PM2.5, Air Pollution, Texas

1 INTRODUCTION

Outdoor air pollution is one of the most significant environmental threats to both human health and ecosystems. Polluted air can cause chronic stress, insufficient physical activity, and exposure to anthropogenic environmental hazards. The World Health Organization reported approximately 3.7 million deaths globally were attributable to ambient air pollution in 2012 (WHO 2016). The deaths from outdoor air pollution are projected to double from the current level by 2050 (OECD 2012). Among many types of air pollutants, particulate matter (PM) has been a growing concern in large cities (Gao et al. 2009; Han et al. 2015). People in urban regions in China especially suffer from the increased level of particle pollution, which at times causes transboundary environmental conflict between neighboring countries due to the pollutants' dispersion properties and the broader airshed. Hong et al. (2019) estimated that about 12,100 Chinese will die each year from $PM_{2.5}$ exposure by 2050, especially with the greater vulnerability of China's aging population that will further increase the estimated deaths from $PM_{2.5}$. In the United States, PM was first regulated by the U.S. Environmental Protection Agency (EPA) under the authority of the Clean Air Act in 1970, along with five other common air pollutants including ground-level ozone (O_3), carbon monoxide (CO), lead, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). The EPA regulates the National Ambient Air Quality Standards (NAAQS) for state and local governments, mandating that they reduce emissions of these pollutants and comply with the standards. These regulatory policies and recent efforts have reduced emissions of PM pollutants and improved overall air quality in U.S. regions (Nolte et al. 2018). However, the effect on large cities with growing populations and impervious urban surfaces has not been well documented.

PM is comprised of a mix of solid particles and liquid droplets found in the air. It has two forms: 1) with aerodynamic diameters larger than 2.5 microns (μm) and smaller than 10 μm course particulates (PM_{10}) and 2) with less than or equal to 2.5 μm in diameter of fine particulates ($PM_{2.5}$). While coarse particulates such as dust, dirt, pollen, and smoke are large and dark enough to be seen with the naked eye, fine particles comprised of a complex mixture of organic and inorganic materials (e.g., combustion particles, metals, chemicals) are very small (i.e., about one-thirtieth that of the average human hair) and only detected using an electron microscope. The major causes of the pollutant include traffic emissions and road dust resuspension (Jin et al. 2014) as well as other direct sources from construction, power plants, and industries. For this reason, built-up areas and industrial zones with many urban activities and predominantly hard surfaces have a significant impact on PM concentrations. Fine PM do not simply stay at the surface of emission sites, but they move up and around in the urban canopy structure. In denser cities, fine PM and other contaminants are frequently trapped in the confined space shaped by a tunnel of skyscrapers, thus increasing the density of $PM_{2.5}$ (Guo 2009; Kaur 2007).

The emphasis on global and national air pollution has shifted from PM_{10} to $PM_{2.5}$ as the latter creates more serious problems associated with the very small size of the particles. It is well known that fine PM air pollution is the leading environmental cause of poor health and premature death (Brook et al. 2010; Kelly and Fussell 2015; Harrison and Yin 2012; Vinzents et al. 2005; Yu 2010). The small inhalable particles can travel deep into the human respiratory system and even into the bloodstream which can cause increased blood pressure and cardiovascular diseases. It may even induce cancer especially in vulnerable populations such as young children and the elderly, potentially reducing their life expectancy.

Fine PM is also an important climate-relevant air pollutant. Along with ground-level ozone precursors (nitrogen oxides and volatile organic compounds), black carbon, which is a component of fine PM, is notable for short-lived climate pollutants. When black carbon is deposited on ice and snow, it causes local warming and increases melting (UNECE 2016). Atmospheric science and metrological studies state that elementary carbon, which is also a fraction of PM, originates mainly from incomplete burning processes (Petzold et al. 2013) and drives global warming by inducing a temperature rise through heat absorption (Andreae and Gelencsér 2006; Jacobson 2001). Nolte et al. (2018) examined the potential impacts of near-term climate change on regional ozone and fine particulate air quality in the continental U.S. regions and found that an increase in $PM_{2.5}$ will be pronounced in the Southeast by 2030 under two climate change scenarios. These changes will be due to an increase in organic matter primarily occurring during the summer and autumn. They also reviewed numerous studies that investigated the impacts of climate change on $PM_{2.5}$ and argued that most studies have neglected changes in climate-sensitive PM emissions sources. They also found that there is little consistency among their findings.

One strand of $PM_{2.5}$ research focuses on clinical evidence that reveals the harmful effects of ambient fine particles on human health (Ghorani-Azam et al. 2016). The other line of research examines the mechanic characterization of the particles such as the movement and transport pattern of the atmospheric fine PM in a given space. Turner and Allen (2008) also assessed the degree of intraurban variability for various physical and chemical properties of $PM_{2.5}$ using field data measurements. They found that secondary formation drives fine PM mass toward high intraurban spatial homogeneity. However, the PM components that are dominated by primary emissions such as black carbon and several trace elements tend to exhibit greater spatial heterogeneity. Most of this research has relied on hypothetical or simulated environments or random street measurement points. Only a handful of studies have examined the relationship between urban form and air quality. For example, Liu et al. (2018) analyzed $PM_{2.5}$, along with other air pollution measures of the air pollution index (API) and exceedance levels, in relation to various urban compositional and configurational metrics for 83 Chinese cities. They found that the pollution level generally increased with a larger city size and varied in different seasons. In particular, compositional metrics such as urban density were positively correlated with $PM_{2.5}$ concentrations for medium and large cities. In addition, configurational metrics (e.g., urban contiguity, urban compactness, and urban patch shape complexity) were negatively correlated exclusively with $PM_{2.5}$ concentrations for megacities. This finding implies that it is important to examine how built-up areas are arranged in relation to $PM_{2.5}$, especially in large cities.

On the mitigation side, some studies have shown the impacts and roles of urban street trees and urban forests on a reduction in $PM_{2.5}$ concentrations (Kennen and Kirkwood 2015; Nowak et al. 2006; Nowak et al. 2013). Jin et al. (2014) utilized a computer simulation to examine the impact of street trees on $PM_{2.5}$ dispersion and found that tree canopy density, leaf area, and the wind speed change rate are significant predicators of $PM_{2.5}$ reduction. Jeanjean et al. (2016) also argued that a green infrastructure can reduce $PM_{2.5}$ traffic emissions on a city scale, particularly stressing that trees and grass have greater effects locally. Their findings showed a 9.0% reduction in $PM_{2.5}$ concentrations from an aerodynamic dispersive effect of trees, 2.8% decrease from deposition on trees (11.8 t year^{1}), and 0.6% from deposition on grass (2.5 t year^{-1}) in a densely built area in the UK. Similarly, Nowak et al. (2006) demonstrated an estimated air quality improvement with 711,000 metric tons ($3.8 billion value) of total annual air pollution removal (O_3, PM_{10}, NO_2, SO_2, CO) from urban trees in 55 U.S. cities. Nowak et al. (2013) also modeled the effect of trees, especially focusing on $PM_{2.5}$ concentrations. They showed the associated health effects for ten U.S. cities, demonstrating the total amount of annual $PM_{2.5}$ removal of trees, which ranged from 4.7 tonnes in Syracuse to 64.5 tonnes in Atlanta. Kennen and Kirkwood (2015) also identified the capabilities of plant species and different types of vegetation including trapping, absorbing, and filtering of the fine PM from the air, emphasizing the phytoremediation performance.

The importance of trees and vegetation as natural solutions to address air pollution in cities has been stressed in both research and practice. The Trust for Public Land Center for City Park Excellence (2008) translated the benefits of parks and open spaces in relation to human health into monetary values by presenting national-level public cost savings and economic benefits. In this manner, the existing literature supports that urban parks and open spaces with tree canopy cover can play a significant role in reducing fine PM in built-up environments, along with other common ecosystem services that they provide (e.g., recreation). However, despite a wide breadth of research related to the subject of fine PM, little research has examined the relationships between spatial morphology of urban green spaces and city-level $PM_{2.5}$ pollution levels in large U.S. cities. The hypothesis of this study is that the quantity and spatial arrangement of urban green spaces are associated with $PM_{2.5}$ concentrations at the city level, regardless of the size of the urban population or city. Using a landscape metrics and spatial morphology analysis approach, we examined the relationships among urban green space patterns, $PM_{2.5}$ concentrations, and meteorological factors in six of the largest cities in Texas in the United States.

2 METHODS

2.1 Research Setting

Texas is one of the most populated and polluted states in the United States. According to the American Lung Association State of the Air, which recently ranked metropolitan areas based on ozone and particle pollution, Texas has two cities in the top 25 most polluted list (Houston and Dallas-Fort Worth). The “triangle” cities of Houston, San Antonio, and Dallas have populations of over 1 million, which makes them one of the 10 most populated cities in the U.S. The next largest cities in Texas are Austin, Fort Worth, and El Paso, which are among the top 25 populated cities in the country. Despite the state’s vast size (the largest state in the continental U.S. by area), most Texans live in and around these urban metropolitan areas. Three related factors of these urban agglomerations have more or less impacted low air quality: 1) high automobile dependency (Frederick 2016), 2) public investment in the car-oriented infrastructure, and 3) urban and suburban sprawl. This study examined the six largest cities in Texas including Houston, San Antonio, Dallas, Austin, Fort Worth, and El Paso (Table 1) to determine the amount and spatial pattern of urban green spaces (e.g., parks, tree canopy cover, and other green spaces) and their associations with citywide fine particle pollution levels.

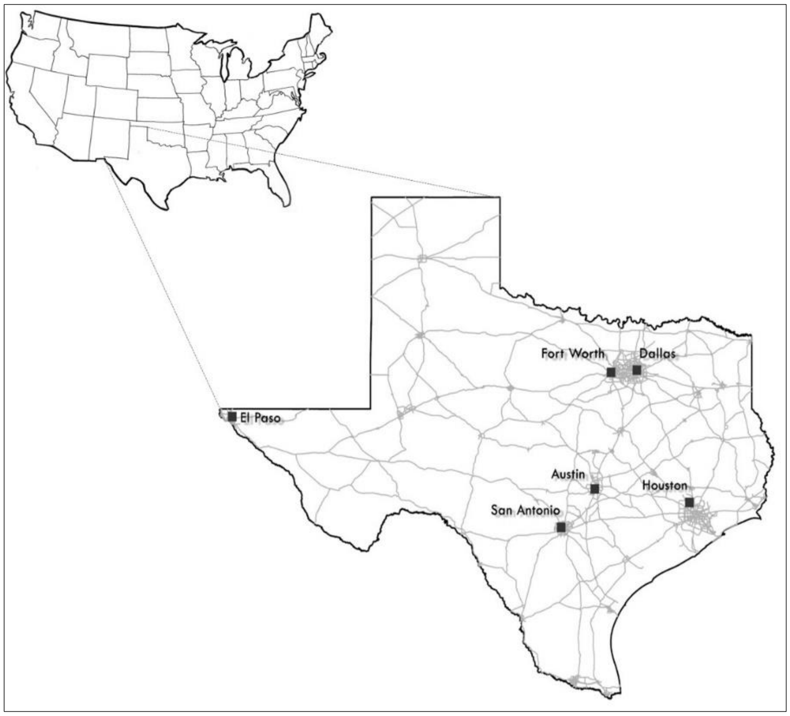

Figure 1. Location of selected Texas cities.

Table 1. City land area and population of the selected six largest cities in Texas.

City	City Land Area (km^2)	Population	Population Density
Houston	1,553	2,099,451	3,501
San Antonio	1,194	1,327,407	2,880
Dallas	8,820	1,197,816	3,518
Austin	7,716	790,390	2,653
Fort Worth	880	741,206	2,181
El Paso	661	649,121	2,543

2.2 Data Collection and Variables

Three groups of variables and relevant datasets were obtained for the statistical analysis. We utilized the 2010 U.S. National Census data for the urban variables including the city land area, city population, and population density. For green space variables, natural land cover layers were extracted from the 2011 data from the USDA national land cover database (NLCD) and combined the data into a single raster layer for the corresponding cities. The green space data were entered as input data into the measurements of two landscape pattern metrics: the “shape” and “connectivity” of the green spaces. This computation process was run through FRAGSTATS (ver. 4.2), a software tool designed to quantify the landscape metrics related to the composition and configuration of the landscape of interest at the patch, class, and landscape levels (McGarigal et al. 2012). We employed the connectance metric (CONNECT) and a shape index, perimeter-area fractal dimension (PAFRAC), for the landscape-level analysis. CONNECT is defined as the number of functional joinings for each pair of green space patches within a certain distance (1,000 m in our analysis), which ranges from 0 (when there is only a single patch or none of the patches of green space are connected) to 100 (when every patch of the green space is connected). The PAFRAC was measured to obtain an overall sense of geometric complexity and compactness of shapes for a collection of green space patches at the city level (Figure. 2). The PAFRAC metric represents a normalized ratio of the patch perimeter to the area in which the complexity of the patch shape is compared to a standard shape (square) of the same size. The PAFRAC value, which ranges from 1 to 2, approaches 1 when the green spaces have simple perimeters, while the fractal dimension is closer to 2 when they are in a highly convoluted form (McGarigal et al. 2012). For the daily meteorological data including ambient temperature and wind speed, the U.S. Environmental Protection Agency Air Data repository served as the primary data source. From the same source, $PM_{2.5}$ daily data ($PM_{2.5}$ FRM/FEM mass) for the year 2010 were collected for the selected cities. The city-wide PM pollution concentrations were the average of the measures of the monitoring sites in each city: 19 stations in Houston, 12 stations in San Antonio, 13 stations in Dallas-Fort Worth, 5 stations in Austin, and 22 stations in El Paso.

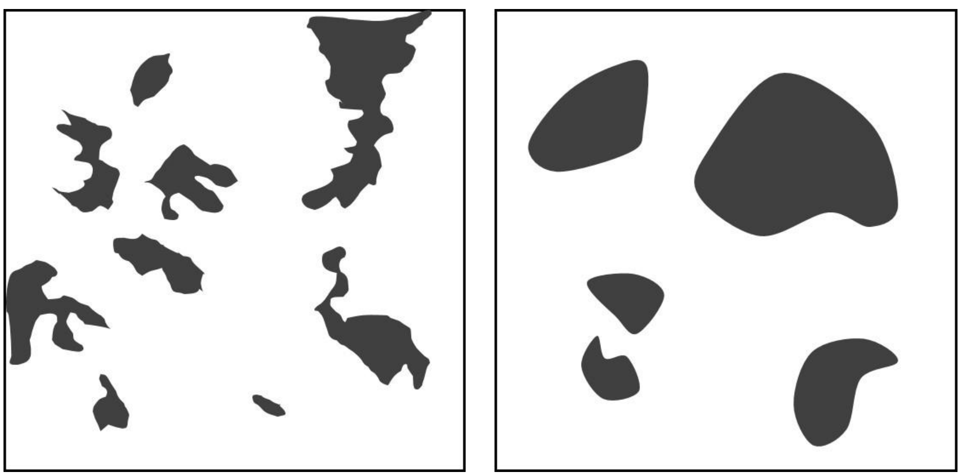

Figure 2. Diagram of two urban areas with higher shape complexity of green space patches (left) vs. lower shape complexity (right).

2.3 Data Analysis

Daily air quality ($PM_{2.5}$ FRM/FEM mass) and meteorological features, such as air temperature and wind speed, were summarized separately for the six urban cities in Texas and then all together based on the descriptive statistics. A bivariate test (e.g., correlation) was performed to explore the relationships of these variables with urban and green space morphology features (i.e., city land area, population, green space [area, %], tree canopy [area, %]). Further, hierarchical linear modeling (HLM) (Raudenbush and Bryk 2002; Singer and Willett 2003) was conducted to estimate the effects of the meteorological features (in level 1: day) and urban features (in level 2: city) on the daily particle pollution level. This process was performed in two settings: (1) with no interaction among the dependent variables and (2) with interaction among the dependent variables. First, the HLM analysis was conducted with no interaction given to simply explore the main effects of the independent variables on the dependent variable, Second, the analysis was conducted with two sets of interactions, 1) temperature and green spaces and 2) temperature and population density, to identify the effects of these interactions on particle pollution, while controlling for all other dependent variables. The interaction was set based on the proven evidence from contemporary studies showing a high correlation between an urban population and temperature (e.g., Maimaitiyiming et al. 2014; Oke 1973) and between green spaces and temperatures (Kim et al. 2016; Maimaitiyiming et al. 2014). The HLM model also accounted for the clustering of particulate measurements within cities. The first-order autoregressive, and the first-order moving-average structure (ARMA[1,1]) was assumed for error covariances to incorporate a spatial metric into the distance function of measurements repeated across locations. Table 2 indicates that the first-order moving-average error structure is the most appropriate (i.e., the lower the AIC, AICC, and BIC criteria, the better the fit to the model) compared to other structures such as the homoscedastic error structure. Restricted maximum likelihood (REML) was employed to estimate the model parameters (e.g., coefficient, intercept). All analyses were conducted using SAS 9.4 (SAS Institute 2002–2012).

Table 2. HLM results of predicting $PM_{2.5}$ with an interaction between temperature and population density and between temperature and green space.

Error structure	AIC	AICC	BIC
Homoscedastic error structure	5858.1	5858.1	5863.0
First-order autoregressive moving-average	5632.8	5632.8	5632.2
Compound symmetry	5860.1	5860.1	5859.7

3 RESULTS

Daily particulate levels, temperature, and wind speed are summarized in Figure 3 for the six cities. When analyzed at the day level, it was found that particle pollution has a significant positive association with temperature (r = 0.14, p < 0.001) and negative association with wind speed (r = –0.30, p < 0.001) (see Table 3). For urban variables, particle pollution was significantly and positively correlated with city land area, population (all r = 0.19, all p < 0.001), and population density (r = 0.08, p < 0.01). Green space and shape complexity (all r = 0.09, all p < 0.01) were also significantly associated with particle matter, while connectivity (r = –0.14, p < 0.001) was negatively and significantly related to particle pollution. Among the independent variables, there were very high correlations of population with city land area (0.96) and population density with population (0.79), which is likely an issue of multicollinearity. This problem occurs because population density includes information about both the city land area and population and thus population was excluded from subsequent HLM analyses.

Table 3. Correlations between air quality, meteorological features, and urban morphology features.

Variable	1	2	3	4	5	6	7	8	9	10
1. Particle pollution ($PM_{2.5}$)	1.00									
2. Temperature (°C)	0.14***	1.00								
3. Winds (knots)	–0.30***	–0.13***	1.00							
4. City land area (Square kilometer)	0.19***	0.07**	–0.13***	1.00						
5. Population (1,000)	0.19***	0.07***	–0.17***	0.96***	1.00					
6. Population density	0.08**	0.06**	–0.21***	0.58***	0.79***	1.00				
7. Green space(Square kilometer)	0.09**	0.05*	–0.21***	0.33***	0.31***	0.20***	1.00			
8. Shape complexity(PAFRAC)	0.09**	0.00	–0.12***	–0.24***	–0.11***	0.07**	0.53***	1.00		
9. Connectivity	–0.14***	–0.06**	0.10***	–0.79***	–0.69***	–0.36***	–0.03	0.70***	1.00	
10. Tree canopy (%)	–0.01	0.05*	–0.23***	0.24***	0.28***	0.34***	0.15***	–0.33***	–0.62***	1.00
M	10.81	67.85	5.08	382.33	1134.23	2.88	72.97	1.41	0.88	24.27
SD	4.68	15.59	2.07	126.66	544.25	0.54	35.22	0.03	0.41	11.41

*$p < 0.05$, **$p < 0.01$, ***$p < 0.00$

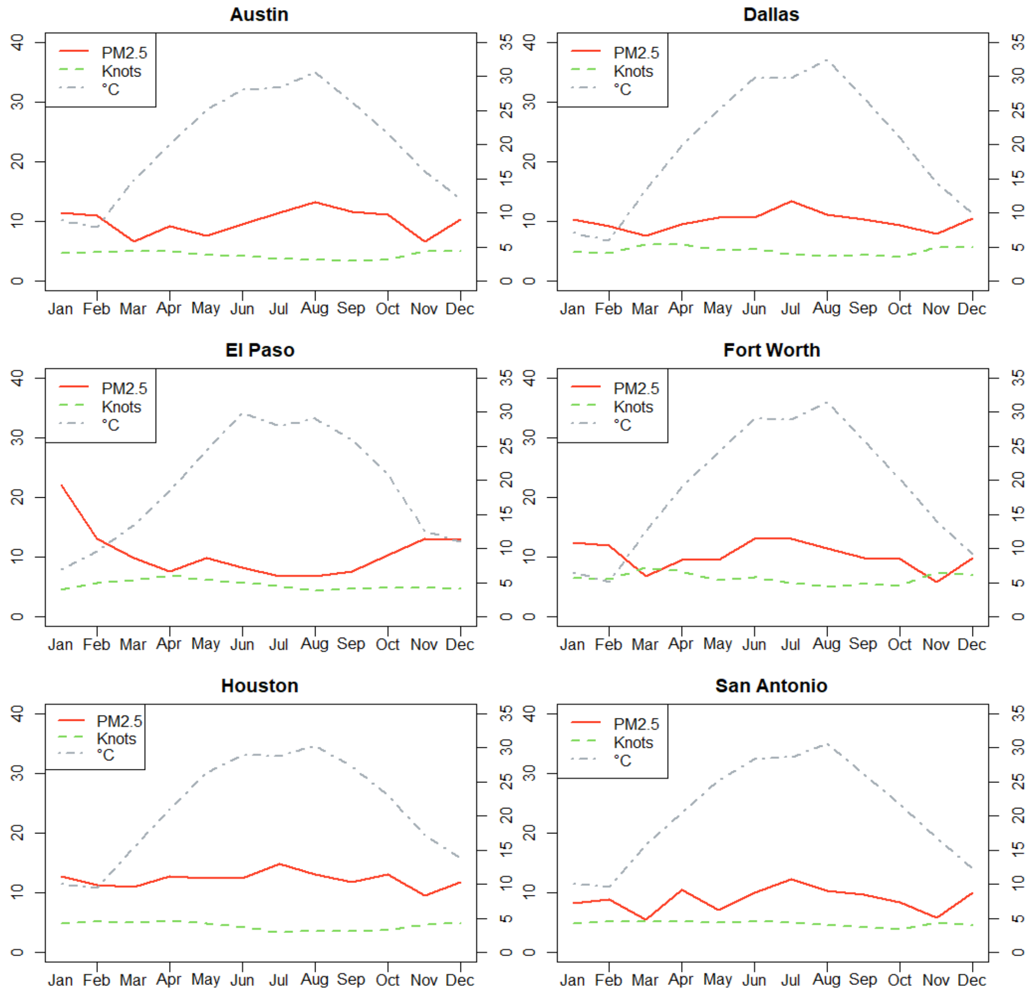

Figure 3. Air quality and meteorological features in 2010 for six Texas cities.
Note: The left y-axis represents the scales for particle pollution ($PM_{2.5}$) and wind (knots); and the right y-axis represents the scale for temperature (°C).

The results of the HLM analysis under the setting of no interaction among the variables is provided in Model 1 of Table 4. Both the temperature and wind speed variables significantly predicted the daily particle pollution level after controlling for other variables in the model. This result suggests that lower temperatures and faster winds are associated with higher air quality (both $p < 0.001$). For urban variables, population density did not significantly predict the daily particle pollution level. However, green space, connectivity and percent of tree canopy were significant predictors of the daily particle pollution level. That is, higher green space, higher connectivity, and a higher tree canopy are related to higher air quality (all $p < 0.05$). In shape complexity, a significant and very high coefficient was reported (58.40), but that does not mean the effect of shape complexity on particle pollution is decisive. This phenomenon was caused by the range of the measurements for shape complexity (PAFRAC) progressing from 1 to 2. The difference between the maximum and minimum values of shape complexity was only 0.0987, which only indicates a small increase of the PM value by 5.76 at the maximum when the shape complexity changed from the minimum to the maximum value.

Model 2 in Table 4 shows the results when interactions between a) temperature and population density and b) temperature and green space were assumed. The directions of the effects of wind, shape complexity, connectivity, and tree canopy on particle pollution were the same as in the previous case (negative direction), and the estimated coefficient values showed only small differences of –0.01, –3.15, 0.18 and 0.01, respectively (all significant). The interaction of temperature and population density after controlling for other variables provided an increasing effect of particle matter ($r = 8.3 \times 10^{-5}$, $p < 0.01$). As Figure 4(a) shows, in the cities with low and medium population density, particle pollution was not greatly affected by temperature changes. However, in the cities with high population density, the particulate matter pollution increased sharply as the temperature increased (steep slope). This indicates that high population density and temperature creates a negative synergy effect on particle pollution. The interaction between temperature and green space with other controlled variables suggested a significant effect on high air quality ($r = –8.8 \times 10^{-4}$, $p < 0.05$). Figure. 4(b) shows that in cities with a low amount of green space, air quality significantly deteriorates as the temperature increases. For cities with a moderate amount of green space, the same pattern was found (e.g., particle pollution level increased as the temperature rose) but the rate of the PM increase was significantly lower (gentle slope) than that of cities with a small amount of green space. Lastly, for the cities with a high level of green space, the particle matter tended to decrease slowly and slightly even if the temperature increased. This finding signifies that having more green spaces in cities with relatively high temperature would likely have a more significant mitigation effect of green spaces.

Table 4. HLM results of predicting $PM_{2.5.}$

	Model 1			Model 2		
Level and variables	Effect	*SE*	*t*	Effect	*SE*	*t*
L1: Temp	0.04**	0.01	2.91	–0.16*	0.07	–2.10
Winds	–0.64***	0.07	–8.96	–0.65***	0.07	–9.18
L2: PD	–0.00	0.00	–0.39	–0.01**	0.00	–3.31
GS	–0.04**	0.01	–3.21	0.02	0.03	0.65
SC	58.40**	19.21	3.04	55.25**	19.32	2.86
CN	–4.44**	1.34	–3.32	–4.26**	1.35	–3.16
TC	–0.08*	0.03	–2.43	–0.07*	0.03	–2.33
Cross-level						
Temp × PD				8.3×10^{-5}**	0.00	3.36
Temp × GS				$–8.8 \times 10^{-4}$*	0.00	–1.99

Notes: Temp = Temperature (°C), Winds in knots, PD = Population density, GS = Green space (Square kilometer), SC = Shape complexity (PAFRAC), CN = Connectivity, TC = Tree canopy (%)

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

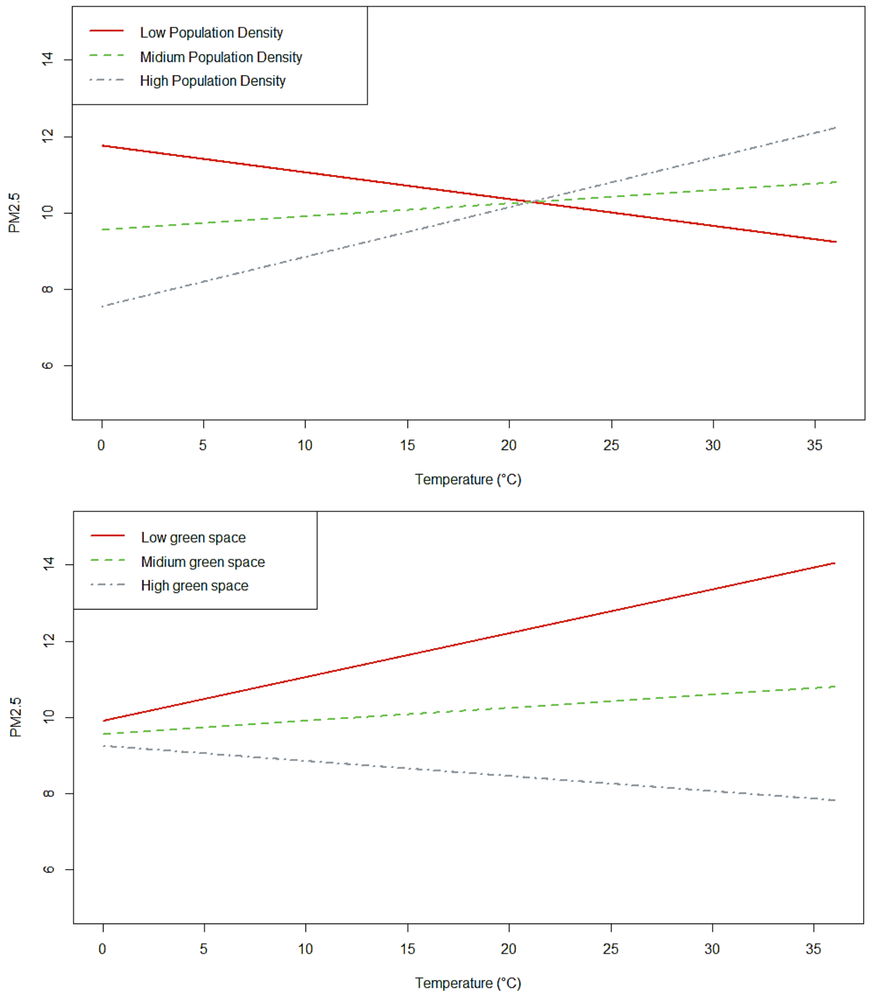

Figure 4. Effect of interaction (a) between temperature and population density (top); and (b) between temperature and green space (bottom) on $PM_{2.5}$.

4 DISCUSSION AND CONCLUSIONS

In summary, the main findings of this study are as follows: a) both ambient temperature and wind speed are highly associated with daily fine particle pollution (a positive association with temperature and a negative association with wind speed); b) when other variables are controlled, city size and urban population are positively correlated with the particle pollution level; and c) green space variables (green space area, green space connectivity, and the percentage of tree canopy coverage) are negatively correlated with the daily $PM_{2.5}$ concentrations for all six cities. Thus, based on the results of the statistical analysis, the hypothesis of this study (i.e., the quantity and spatial arrangement of urban green spaces are associated with $PM_{2.5}$ concentrations at the city level) can be accepted. Furthermore, the temperature-pollution relationship was more pronounced in cities with higher population density and with more green spaces. In other words, when the air pollution increased due to rising temperatures, the cities with higher population density were more impacted. Likewise, even if particle pollution increased with rising temperatures, the rate of the pollution increase slowed in cities with more green spaces, or the pollution level decreased even if the temperature increased.

The implications of this study are of particular significance to large developed and developing cities, as they often have high population density and have building/street canyons that easily trap polluted air. The intricacies of large U.S. cities need to be well understood to address city-level air pollution since these areas have a large number of potentially impacted people and have land use changes that are contributing to rising temperature at the scale of cities. Although some large cities have complied with air quality standards and have best practices in pollution control, the probability of a “climate penalty” (Rasmussen et al. 2013; Wu et al. 2008) cannot be ruled out. The deterioration of air quality due to climate-driven changes could occur more frequently as we have often observed with wildfires (Spracklen et al. 2009; Val Martin et al. 2015) and dust storms (Achakulwisut et al. 2018) caused by warmer temperatures and earlier snowmelt associated with climate change. These natural disasters, in turn, create high concentrations and variability of fine particles (Nolte 2018).

Connected green spaces are also important in order to alleviate the impact of fine particulate matter in large cities with urban warming and growing populations. Our findings identify green morphological features as a mitigation predictor of urban air pollution. To mitigate these urban air pollution problems in already built-up urban areas, it is imperative to designate additional open green spaces so they are interconnected in the large urban landscape. Urban renewal, city-wide landscape planning, and landscape urbanism types of urban design interventions provide opportunities to help reconfigure the urban form with more green spaces and prevent green space fragmentation. These changes are conducive to reducing city-level particle pollution. In addition, promoting green space performance that increases the amount and continuity of spaces with trees and vegetation can help solve urban air pollution problems. Cities can also leverage the existing mitigation efforts to greenify built areas and emission source management (e.g., use of alternative fuels and installing filters and dust collectors). Broader impacts of the study include increased urban resilience to pollution sensitivity, enhanced public awareness about the roles of green spaces on changing urban climate, and potential changes in planning and policy practices that encourage park development and urban greening efforts in a holistic framework, rather than a discrete site-level approach.

This study reinforces the existing body of research that highlights the effects of green spaces on fine PM levels and suggests that creating highly connected and concentrated green spaces is a desirable spatial pattern to maximize the green space effects in urban areas. However, urban air quality is a complex and challenging issue. The collective capacity and performance of green spaces in urban environments may differ depending on site-specific characteristics such as plant type and species, leaf areas, and other micro-climatic components. In addition, to better understand the complex pattern of the fine PM effects in large cities, more sophisticated designs for data analysis with additional environmental and micro-climate variables are needed. Given that the cities in this study have higher concentrations of crime that presumably affect connectivity of green spaces, future research is needed to take into account the secondary variables related to urban socioeconomic characteristics. Although we utilized the best available daily fine particles data for this pilot study, there may be inherent errors resulting from the number and location of monitoring stations. Nevertheless, this study highlights the importance of green spaces in the context of quantity and spatial configurations as a fundamental building block to create cleaner cities.

REFERENCES

Achakulwisut, P., Mickley, L.J. and Anenberg, S.C. (2018) Drought sensitivity of fine dust in the US Southwest: Implications for air quality and public health under future climate change. *Environmental Research Letter,* 13, 054025

Andreae, M.O. and Gelencsér, A. (2006) Black carbon or brown carbon? The nature of light-absorbing carbonaceous aerosols. *Atmospheric Chemistry and Physics,* 6, 3131–3148

Brook, R.D., Rajagopalan, S., PopeIII, C.A., Brook, J.R., Bhatnagar, A., Diez-Roux, A.V., Holguin, C., Hong, Y., Luepker, R.V., Mittleman, M.A., Peters, A., Siscovick,D., SmithJr, S.C., Whitsel, L. and Kaufman, J.D. (2010) Particulate matter air pollution and cardiovascular disease. *Journal of the American Heart Association*, 2331–2378

Frederick, C.P. (2016) *Constructing Urban Life: A Study of Automobile Dependency in 148 Did-size U.S. Cities*. Ph.D. Dissertation in Urban and Public Affairs, University of Louisville

Ghorani-Azam, A., Riahi-Zanjani, B. and Balali-Mood, M. (2016) Effects of air pollution on human health and practical measures for prevention in Iran. *Journal of Research in Medical Sciences*, 21, 65

Guo, Y., Jia, Y., Pan, X., Liu, L. And Wichmann, E. (2009) The association between fine particulate air pollution and hospital emergency room visits for cardiovascular diseases in Beijing China, *Science of the Total Environment,* 407, 4826–4830

Han, L., Zhou, W., Li, W., Meshesha, D.T., Li, L. and Zheng, M. (2015) Meteorological and urban landscape factors on severe air pollution in Beijing. *Journal of the Air & Waste Management Association*, 65, 782–787

Harrison, R.M. and Yin, J. (2000) Particulate matter in the atmosphere: which particle properties are important for its effects on health? *Journal of Science of the Total Environment*, 249, 85–101

Hong, C., Zhang, Q., Zhang, Y., Davis, S.J., Tong, D., Zheng, Y., Liu, Z., Guan, D., He, K. and Schellnhuber, H.j. (2019) Impacts of climate change on future air quality and human health in China. *Proceedings of the National Academy of Sciences*, 116, 17193–17200

Jacobson, M.Z. (2001) Strong radiative heating due to the mixing state of black carbon in atmospheric aerosols. *Nature,* 409, 695–697.

Jeanjean, A.P.R., Monks, P.S. and Leigh, R.J. (2016) Modelling the effectiveness of urban trees and grass on $PM_{2.5}$ reduction via dispersion and deposition at a city scale. *Atmospheric Environment*, 147, 1–10

Jin, Si., Guo, J., Wheeler, S., Kan, L. and Che, S. (2014) Evaluation of impacts of trees on $PM_{2.5}$ dispersion in urban streets. *Atmospheric Environment,* 99, 277–287

Kaur, S., Nieuwenhuijsenb, M.J. and Colvile, R.N. (2007). Fine Particulate Matter and Carbon Monoxide Exposure Concentrations in Urban Street Micro Environment. *Atmospheric Environment,* 41, 4781–4810

Kelly, F.J. and Fussell, J.C. (2015) Air pollution and public health: Emerging hazards and improved understanding of risk. *Environmental Geochemistry and Health,* 37, 631–649

Kennen, K. and Kirkwood, N. (2015) *Phyto: Principles and Resources for Site Remediation and Landscape Design*. Routledge: New York

Kim, J., Gu, D., Shon, W. and Kil, S. (2016) Neighborhood Landscape Spatial Patterns and Land Surface Temperature: An Empirical Study on Single-Family Residential Areas in Austin, Texas. *International Journal of Environmental Research and Public Health*, 13, 880

Liu, Y., Wu, J., Yu, D. and Ma, Q. (2018) The relationship between urban form and air pollution depends on seasonality and city size. *Environmental Science and Pollution Research,* 25, 15554–15567

Maimaitiyiming, M., Ghulam, A., Tiyip, T., Pla, F., Latorre-Carmona, P., Halik, U., Sawut, M. and Caetano, M. (2014) Effects of Green Space Spatial Ppattern on Land Surface Temperature: Implications for Sustainable Urban Planning and Climate Change Adaptation. *Journal of Photogrammetry and Remote Sensing,* 89, 59–66

McGarigal, K., Cushman, S.A. and Ene, E. (2012) FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps. University of Massachusetts, Amherst. http://www.umass.edu/landeco/research/fragstats/fragstats.html

Nolte, C.G., Spero, T.L., Bowden, J.H., Mallard, M.S. and Dolwick, P.D. (2018) The potential effects of climate change on air quality across the conterminous US at 2030 under three representative concentration 0athways. *Atmospheric Chemistry Physics,* 18, 15471–15489

Nowak, D.J., Crane, D.E. and Stevens, J.C. (2006) Air Pollution Removal by Urban Trees and Shrubs in the United States. *Urban Forestry & Urban Greening,* 4, 115–123

Nowak, D.J., Hirabayashi, S., Bodine, A. and Hoehn, R. (2013) Modeled $PM_{2.5}$ removal by trees in ten U.S. cities and associated health effects. *Environmental Pollution,* 178C. 395–402

OECD (Organization for Economic Co-operation and Development). (2012) *OECD Environmental Outlook to 2050: The Consequences of Inaction*, OECD Publishing, Paris

Oke, T.R. (1973). City Size and the Urban Heat Island. *Atmospheric Environment,* 7, 769–779

Petzold, A., Ogren, J.A. and Fiebig, M. (2013) Recommendations for the interpretation of "black carbon" measurements. *Atmospheric Chemistry and Physics,* 13, 8365–8379

Rasmussen, D. J., Hu, J., Mahmud, A. and Kleeman, M.J. (2013) The ozone-climate penalty: past, present, and future, *Environmental Science and Technology,* 47, 14258–14266

Raudenbush, S.W. and Bryk, A.S. (2002) *Hierarchical Linear Models: Applications and Analysis Methods*, Sage Publications, Thousand Oaks, CA

SAS Institute (2002–2012). SAS/STAT 9.4 user's guide. SAS Institute Inc, Cary, NC.

Singer, J.D. and Willett, J.B. (2003) *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*, Oxford University Press, New York

Singh, A., Rajput, P., Sharma, D., Sarin, M.M. and Singh D. (2014) Black Carbon and Elemental Carbon from Postharvest Agricultural-Waste Burning Emissions in the Indo-Gangetic Plain. *Advances in Meteorology*, 179301. doi.org/10.1155/2014/179301

Spracklen, D.V., Mickley, L.J., Logan, J.A., Hudman, R.C. Yevich, R., Flannigan, M.D. and Westerling, A.L. (2009) Impacts of climate change from 2000 to 2050 on wildfire activity and carbonaceous aerosol concentrations in the western United States. *Journal of Geophysical Research*, 114, D20301

The American Lung Association (2018) State of the Air Report: Chicago, Illinois

The Trust for Public Land (2008) Center for City Park Excellence. https://www.tpl.org/keywords/center-city-park-excellence

Turner, J. and Colbeck, I. (2008) Physical and Chemical Properties of Atmospheric Aerosols. *Journal of Air Waste Management Association,* 58, 196–215

Turner, J.R. and Allen, D.T. (2008) Transport of Atmospheric Fine Particulate Matter: Part 2—Findings from Recent Field Programs on the Intraurban Variability in Fine Particulate Matter. *Journal of the Air & Waste Management Association,* 58, 196–215

UNECE (United Nations Economic Commission for Europe) and Climate Change (2016) United Nations Economic Commission for Europe. https://www.unece.org/index.php?id=42546

Val Martin, M., Heald, C.L., Lamarque, J.F., Tilmes, S., Emmons, L.K. and Schichtel, B.A. (2015) How emissions, climate, and land use change will impact mid-century air quality over the United States: A focus on effects at national parks. *Atmospheric Chemistry and Physics*, 15, 2805–2823

Vinzents, P.S., Møller, P., Sørensen,M., Knudsen, L.E., Hertel, O., Jensen, F.P., Schibye, B. and Loft, S. (2005) Personal Exposure to Ultrafine Particles and Oxidative DNA Damage. *Environmental Health Perspectives*, 113, 1485–1490

World Health Organization (2016) Ambient air pollution: A global assessment of exposure and burden of disease. https://www.who.int/phe/publications/air-pollution-global-assessment/en/

Wu, S., Mickley, L.J., Leibensperger, E.M., Jacob, D.J., Rind, D. and Streets, D.G. (2008) Effect of 2000–2050 global change on ozone air quality in the United States. *Journal of Geophysical Research*, 113, D06302

Xing, Y.F., Xu, Y.H., Shi, M.H. and Lian, Y.X. (2016) The impact of PM2.5 on the human respiratory system. *Journal of Thoracic Disease,* 8, E69–E74