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Does Urban Form Affect Urban NO_2? Satellite-Based Evidence for More than 1200 Cities

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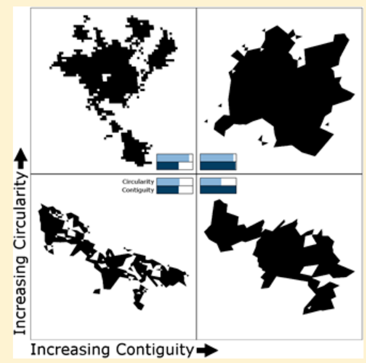
Supporting Information

ABSTRACT: Modifying urban form may be a strategy to mitigate urban air pollution. For example, evidence suggests that urban form can affect motor vehicle usage, a major contributor to urban air pollution. We use satellite-based measurements of urban form and nitrogen dioxide (NO_2) to explore relationships between urban form and air pollution for a global data set of 1274 cities. Three of the urban form metrics studied (contiguity, circularity, and vegetation) have a statistically significant relationship with urban NO_2; their combined effect could be substantial. As illustration, if findings presented here are causal, that would suggest that if Christchurch, New Zealand (a city at the 75th percentile for all three urban-form metrics, and with a network of buses, trams, and bicycle facilities) was transformed to match the urban form of Indio - Cathedral City, California, United States (a city at the 25th percentile for those same metrics, and exhibiting sprawl-like suburban development), our models suggest that Christchurch's NO_2 concentrations would be ~60% higher than its current level. We also find that the combined effect of urban form on NO_2 is larger for small cities ($\beta \times \mathrm{IQR} = -0.46$ for cities < ~300 000 people, versus −0.22 for all cities), an important finding given that cities less than 500 000 people contain a majority of the urban population and are where much of the future urban growth is expected to occur. This work highlights the need for future study of how changes in urban form and related land use and transportation policies impact urban air pollution, especially for small cities.



INTRODUCTION

More than half of the world population, 3.9 billion people (54%) in 2014, live in urban areas, with an additional 2.5 billion urban dwellers expected by 2050.[1] Cities serve as economic and social centers, concentrating people, activities, ideas, and industries. Cities may also concentrate environmental hazards such as air pollution, and potentially health inequities.[2,3] As such, cities are a focal point for understanding and addressing environmental health issues. Urban air pollution is responsible for millions of deaths each year globally, and is one of the top ten causes of death in the United States.[4] Mortality estimates from the Global Burden of Disease are predominately attributed to fine particles. On the other hand, the International Agency for Research on Cancer classifies outdoor air pollution (i.e., as a mixture, rather than a single pollutant) as the leading environmental carcinogen.[5] Urban air quality has generally improved for most developed countries, but worsened in most developing countries owing to rapid urban growth, increased automobile usage and congestion, and often lax environmental regulation.[6−9]

Transportation is one of the largest contributors to urban air pollution for pollutants such as carbon monoxide, nitrogen oxides, benzene, ozone, and fine particulate matter ($PM_{2.5}$).[10,11] For example, recent estimates suggest that globally, approximately 25% of ambient urban $PM_{2.5}$ is attributable to motor vehicles.[12] Strategies to reduce motor vehicle use may play a role in improving urban air quality. Evidence suggests that changes in urban form can impact travel behavior such as travel distance, trip frequency, and mode choice.[13−19] For example, increasing population density is associated with a decrease in per capita daily vehicle-miles traveled (VMT) and an increase in walking and biking trips.[16−21] Dense neighborhoods with mixed land uses may be more accommodating to shorter trips and alternative modes of transportation (e.g., walking, biking, mass-transit) while also presenting barriers or disincentives to driving (e.g., limited parking, higher parking costs, congestion).[17,21] Similarly, the development of alternative transportation infrastructure may increase demand for nearby residential and retail property and consequently increase density.[22−24]

The existing literature suggests that increased density and other built environment characteristics (e.g., compactness, contiguity, centrality) are associated with lower air pollutant concentrations.[25−31] Empirical investigations of the relationship between urban form and air pollution are mostly limited to cities in developed countries (primarily in the United States) and tend to focus on large cities. Yet the majority of the world's

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urban population lives in small cities (fewer than 500 000 people) and most of the future urban growth is expected to occur in small cities and developing countries.[1] A study of 83 global cities found that all else equal, more-contiguous urban form is associated with lower concentrations,[27] a similar finding to U.S.-only studies.[30] More recently, Larkin et al. investigated 830 cities in East Asia during 2000−2010 and found that changes in urban form (determined, e.g., via lights at night, impervious surfaces, population density) were associated with changes in air quality.[31] They reported that the urban form−air quality relationship varies with city population; increasing population while limiting urban land growth may attenuate or decrease per capita emissions.[31] These studies are few in number, yet illustrate the potential importance of urban form as a tool for improving air quality. The existing literature encourages further exploration of these relationships and how they may vary globally. To date, most studies of urban form and air pollution in developing countries have focused on East Asia. It is still unknown whether urban form−air quality relationships hold for low income countries globally, and to what degree differences in national policy may impact these relationships. Additionally, in their analysis of East Asian cities, Larkin et al. found evidence that ideal urban form typologies vary by city population size; this finding may be true in other regions, but to our knowledge, it has not been previously studied.

Here we employ satellite-based measurements of nitrogen dioxide (NO_2, a proxy for traffic-related air pollution and a major constituent of urban air pollution)[6] and a global data set of 1274 urban areas[32] to explore the relationship between urban form and air quality. Our work builds on prior research by employing a much larger sample of global cities, allowing for the exploration of factors (i.e., city population, country-level income, environmental performance and policy) that may influence the relationship between urban form and air quality. In this work we are able to explore how urban form - air quality relationships vary for a consistent set of cities in low- and high-income countries, giving insight into the impacts of urban form in developing countries where existing literature is limited. Additionally, more than half of the cities in our data set (n = 675 cities; 53% of all cities) are small cities (100 000−500 000 people), allowing us to explore the relationship of urban form and air pollution for a large global sample of small cities.

■ MATERIALS AND METHODS

We study NO_2, a major constituent of urban air pollution. NO_2 also serves as a marker for a suite of pollutants linked to traffic and other combustion related emissions,[33] and as a useful proxy for urban air pollution owing to its relatively short lifetime (~hours) that makes it indicative of localized emissions. NO_2 is associated with several adverse health outcomes, including aggravation of respiratory diseases,[34,35] increased hospitalization and emergency room visits,[36] incidence of asthma,[37] mortality,[33,38−40] and lung cancer.[41] NO_2 is a criteria air pollutant regulated by the U.S. Environmental Protection Agency , as well as a precursor to secondary particle formation, photochemical ozone production, and acid rain. Therefore, NO_2 is well suited for the exploration of urban form and urban air pollution undertaken here.

We employ publicly available global estimates of gridded ($0.1° \times 0.1°$ [$\sim 11 \times 11$ km^2 at the equator]) annual surface NO_2 concentrations. A detailed description of these data are provided elsewhere.[6] Briefly, tropospheric column NO_2 measurements from three satellite-based instruments (GOME, SCHIAMACHY, and GOME-2) are combined with a global chemical transport model to estimate annual surface NO_2 concentration over a 17 year period (1996−2012).[6] This method of estimating surface NO_2 from satellite measurements has been shown to capture within-urban variability and has been previously used to explore global aspects of urban NO_2 concentrations.[27,42,43] To reduce effects of interannual variability we average three years of surface NO_2 estimates (2000−2002; corresponding to the three years nearest to the built-up area measurements). Satellite measurements of air pollution offer global coverage, and consistent data quality with uniform methodology across cities and regions, and have proven to be a useful tool for exploring urban air pollution globally.[7,9,27,31,43] Estimates of NO_2 surface concentrations derived via satellite measurements are typically lower than 24 h average in situ measurements for several reasons, including satellite measurements occur during daytime hours when NO_2 concentrations can be comparatively low; satellite measurements represent spatially averaged concentrations whereas point-based measurements may capture nearby sources; chemical interferences from most in situ monitors that may positively bias those estimates; and, potential underestimation of NO_2 surface-to-column ratios in urban areas due to model spatial resolution.[42] Nevertheless, satellite-based estimates of NO_2 have been shown to capture the spatial variability of surface concentrations,[42] and are well suited for exploring the relative differences in concentration among urban areas.[27,31,43]

We previously explored the relationship between urban form and air pollution for a globally stratified sample of 83 cities.[27] To our knowledge, that was the first global exploration of this relationship. Our prior study employed built-up area estimates (derived from 30 m Landsat imagery) provided by the World Bank Dynamics of Global Urban Expansion Study.[44] The number of cities provided by the World Bank Study was limited, owing to the time and cost of processing additional cities. The small sample size in the earlier study prevented us from exploring several underlying factors that may influence the urban form−air pollution relationship.

Here, we investigate the urban form - air pollution relationship in greater depth using published estimates of built-up urban area for 1274 global cities.[45] Built-up area was determined by supervised classification of 500 m Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data for years 2001−2002.[46] Potere et al. recently compared ten global maps of urban land cover circa year-2000 and found the MODIS 500 m (MOD500) data employed here to be the most accurate.[47] We therefore trade spatial fidelity of built-up area estimates (30 m previously versus 500 m here) for a much larger sample of cities (83 previously, 1274 cites here). Angel et al. clustered built-up areas if the distance between centroids of nearest-neighbor pixels was less than a maximum distance threshold, and resulting urban clusters were paired with a database of named large cities (at least 100 000 people) to create a data set of 3646 global cities;[32] as described below, we analyzed 1274 of the 3646 cities. The data set also includes year-2000 population for each urban cluster, total built-up urban area, and a measure of the circularity of each city's built-up area.

The four urban form metrics considered here, and described next, are circularity, contiguity, percent vegetation, and percent impervious surfaces. Angel et al. calculated circularity via the proximity index (hereinafter referred to as "circularity"), a

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measure of urban compactness (value range: 0−1; value for a perfect circle: 1) quantifying the relative closeness of the entire built-up area within a city to its geographic center.[32] The proximity index is the ratio of the average distance from all points in an equal-area circle to its center (two-thirds of the radius of the equal-area circle) and the average distance to the centroid of each urban cluster from all built-up pixels in the cluster.[48] Assuming a monocentric city, a circular footprint offers the shortest average distance to the city center and closer proximity of people in the periphery and activities in the urban core. A city exhibiting this type of compactness may indicate a more efficient use of urban area, and may induce fewer and shorter vehicle trips. In addition to the provided circularity index, we derive a contiguity index (value range: 0−1), calculated as the ratio of the largest contiguous polygon of built-up area pixels to the total built-up area for a given city. Large amounts of leapfrog or exurban development, and polycentricism (particularly with satellite cities) would result in a low contiguity index. This type of development could increase the average distance between origins and destinations, as well as create multiple destination centers that may not be centrally located. Therefore, less contiguous cities may be less easily served by public transit, and could induce more automobile traffic and longer travel distances.

Figure 1 shows built-up urban area estimates for three of the 3646 cities, contrasting the MOD500 built-up estimates employed in this analysis (shown left) with built-up estimates

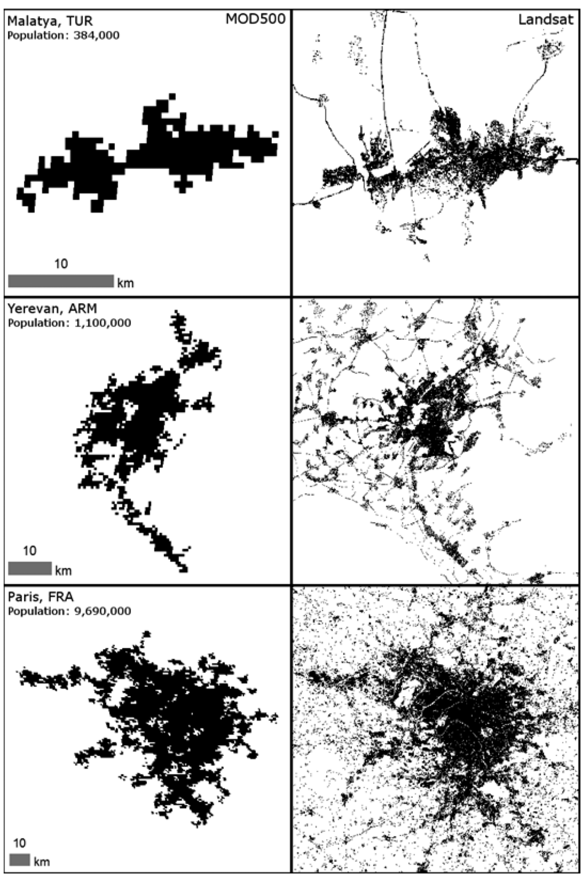

Figure 1. Urban extents for three cities (small, medium, and large), illustrating built-up urban area estimates from the 500 m MODIS data (left) employed here and the 30 m Landsat data (right) employed in Bechle et al. 2011.[27]

from finer resolution (30 m) Landsat imagery (shown right) employed in our prior work. This figure illustrates that the MOD500 built-up area generally captures the geometric form of the primary built-up area, yet the Landsat imagery clearly captures roadways, small patches of urban discontinuity, and small pockets of suburban and exurban developments that the MOD500 data set cannot. The coarse features of the MOD500 data set are the result of its large pixel size (∼500 m), as evidenced by better representation for the larger cities in Figure 1. The MOD500 also suffers from apparent generalization (i.e., the reduction in detail of mapping features) from converting the built-up features to a Google Earth platform. Nevertheless, the MOD500 is, to our knowledge, the largest collection of built-up area estimates for a global database of cities, providing information for ∼40× more cities than the Landsat data set employed in our previous study (3636 cites [MOD500] versus 83 cities [Landsat]).[45] One aspect of this trade-off is that the interpretation of the urban form metrics may change when the resolution of the underlying built-up area estimates change. For example, the maximum distance threshold Angel et al. used to cluster urban pixels in the MOD500 data set is a function of total built-up area (eq 1):

$$D = 649.21\ln(A) - 5234.6 \tag{1}$$

where D is the distance threshold (units: meters) and A is the cluster size (hectares). From this equation we determine that cities with less than ∼50 km^2 of total built-up area are only comprised of a single cluster.[32]

Consequently, analyses here only include cities larger than 50 km^2, where we are less concerned about the contiguity metric being impacted by pixel size. This approach leaves 1303 cities of the 3624 cities. An additional 29 cities were removed owing to missing air pollution data, resulting in 1274 cities for this analysis: ∼35% of cities comprising ∼72% of the total population in the MOD500 database, yet still an order of magnitude more cities than the higher resolution Landsat database.

The circularity metric was calculated differently for the Landsat versus the MOD500 cities. (The Landsat database calculated the ratio of built-up area to total buildable area in a circle circumscribing the main built-up area of the city.) There is low correlation between metrics derived from the MOD500 and 30 m Landsat built-up area estimates (r = 0.35 and 0.31 for circularity and contiguity, respectively) for the 63 common cities in each data set, illustrating that the MOD500 and Landsat based metrics capture different urban spatial characteristics. Therefore, for questions considered here, direct comparisons between analyses employing MOD500 versus Landsat[27] cannot be made. Figure 2 shows built-up urban area and the urban form metrics for four similarly sized (∼200 km^2) cities from the database of the 1274 cities analyzed.

We also employ satellite-based estimates of impervious surfaces[49] and vegetative cover[50] in order to quantify the average percentage of built-up area occupied by impervious surfaces and vegetative cover within each city. These data provide continuous estimates of the percentage of impervious surfaces and vegetative cover at 1 km and 500 m resolution, respectively. For each city, we calculate the average percent coverage for grid cells overlapping the built-up area. The impervious surfaces data employs population and satellite-based lights at night to estimate impervious surfaces.[49] The impervious surfaces data and underlying lights at night data are associated with density (e.g., population, residential,

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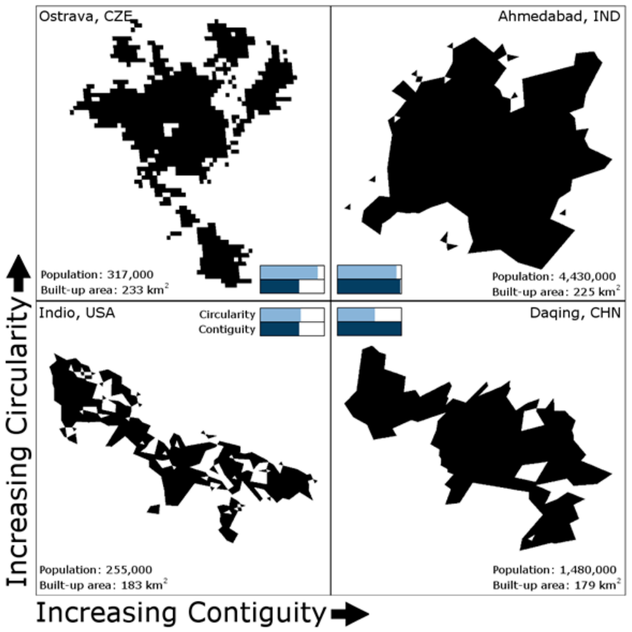

Figure 2. Characteristic cities illustrating contiguity (urban patchiness) and circularity based on 500 m MODIS built-up area (shown in black). Bar charts illustrate contiguity and circularity indices (range: 0−1) for each city.

business) and economic activity.[51] Increased impervious surfaces estimates are also associated with increased land surface temperature, a phenomenon known as the urban heat island effect.[52] Vegetative cover may capture several different urban aspects including (1) fewer land uses with sources, (2) vegetative attenuation of the heat island, and (3) suburban land uses. For the cities in this study, impervious surface and vegetative cover exhibit modest correlation (r = −0.20), suggesting that these two metrics capture different aspects of urban form.

We employ country-level gross domestic product (GDP) per capita (hereinafter referred to as "income") using a three-year mean for the years corresponding to the air quality data (2000−2002; reported in 2005 USD),[53] to account for differences in economic development. Finally, we include several meteorological metrics: (1) harmonic mean of dilution rate (product of wind-speed and mixing height)[54] to account for differences in atmospheric dilution, (2) annual solar insolation[55] to account for differences in the chemical lifetime of NO_2 (primarily chemical loss of NO_2 is to nitric acid, which is sensitive to sunlight and temperature),[56,57] and (3) the percent of days with significant rainfall (≥0.1 mm)[58] to account for potential differences in wet deposition. Summary statistics for all variables are in Supporting Information (SI) Table S1 of the online supplement.

We create linear regression models for the logarithm of arithmetic mean NO_2 concentration in each city to determine the dependence of urban NO_2 concentration on the urban characteristics described above. The population and income metrics were found to be logarithmically distributed; we therefore employ logarithm of population and logarithm of income in our model as the population and income metrics in our model. In addition to our core model, we create several submodels, using the same variables as our full model, with subsets of cities based on tertiles of income, city population, and environmental performance (see below) in order to explore how these factors may impact the effect of urban form on urban NO_2. We employ the GDP per capita metric from above for income tertiles (cut points: $1,980; $22,000), and urban population for city size tertiles (cut points: 289 000 people; 788 000 people). We employ the Yale 2008 Environmental Performance Index (EPI)[59] as a quantitative indicator of environmental policies and outcomes[60] (tertile cut points: 72.5; 81.0). The EPI is a country-level index based on 25 performance indicators whose value ranges from 39.5 (Angola) to 95.5 (Switzerland), with increasing values associated with better environmental performance. The 2008 EPI is the earliest edition of the EPI, and based on data covering several years (~2000−2010).[59] As a sensitivity analysis of our submodels, we also explore models with interaction terms between the three factors (log[income], log[population], EPI) and the urban form metrics.

We employ Monte Carlo coefficient/p-value/sample-size (CPS) charts as both a sensitivity analysis to explore the strength of the predictors included in the core model, and to aid in interpretation of subsample modeling results. Monte Carlo CPS charts summarize coefficients and p-values for submodels created from Monte Carlo random sampling at a range of sample sizes.[61] Here, we employ Monte Carlo random sampling (500 iterations) for n = 100 to 1200 cities at intervals of 100 cities, and report the CPS charts for all of the predictors included in the core model.

■ RESULTS

Our core model, including all 1274 cities, captures 59% of the variation in the dependent variable (logarithm of satellite-derived NO_2 concentration). This simple yet powerful model

Table 1. Linear Regression Model for Logarithm of Mean Urban NO_2

parameter[a]	units	β	SE	$P > t$	$\beta \times$ IQR	partial-R^2
annual insolation	W/m^2	-1.9×10^{-02}	7.4×10^{-04}	<0.001	−1.09	0.34
log[income]	log[Y2005 US$]	0.31	0.02	<0.001	1.02	0.45
% days of rain	%	-2.4×10^{-02}	1.7×10^{-03}	<0.001	−0.50	0.52
log[pop]	Log[person]	0.67	0.06	<0.001	0.45	0.58
dilution rate	m^2/s	-1.7×10^{-04}	5.0×10^{-05}	<0.001	−0.03	0.58
contiguity	unitless (0−1)	−0.48	0.15	0.001	−0.07	0.59
circularity	unitless (0−1)	−0.67	0.22	0.003	−0.09	0.59
% vegetation	%	-7.1×10^{-03}	2.6×10^{-03}	0.007	−0.06	0.59
% impervious	%	-2.4×10^{-03}	1.8×10^{-03}	0.19	−0.05	0.59
_constant	log[ppb]	−0.71	0.49	0.15		

[a]Variables listed by order selected into a forward stepwise (p > 0.05) model.

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offers useful insights into the relationship between urban form and air pollution, and offers a basis of comparison for submodel explorations. Table 1 summarizes model parameters for this core model. SI Table S2 shows pairwise correlations between model parameters. We employ variance inflation factor as a test of multicollinearity (VIF < 1.9 for all parameters). The coefficient plots (shown as $\beta \times$ IQR) and p-value plots shown in Figure 3 illustrate the strength of the predictors included in the core model. As sample size increases, the coefficients converge on the final model coefficient. Moreover, for all significant predictors (all but impervious surfaces) the p-value decreases with increasing sample size, indicating a clear signal from these variables. The large number of cities needed in the model for the urban form metrics to be statistically significant (n > ~1000) illustrates the utility of this large database of cities, as well as the utility of high resolution built-up area data sets that have indicated significant urban form effects with smaller sample sizes.[27,31]

Of the urban characteristics (i.e., log[population] and urban form metrics), log[population] had the largest effect ($\beta \times$ IQR = 0.45) with higher population associated with worsened air quality. Increased urban contiguity, circularity and vegetation metrics are significantly (p < 0.008) associated with lower urban NO_2 concentrations. The impervious surfaces metric has a nonsignificant effect (p = 0.19) on urban NO_2. The magnitude of the effect size of the three significant urban form metrics are small relative to log[population] ($\beta \times$ IQR: −0.06 to −0.09), however, their combined effect could be large. For example, if results presented here are causal, a city with circularity, contiguity and vegetation metrics at the 75th percentile could, on average, accommodate approximately twice the population of a city with these metrics at the 25th percentile while maintaining similar air quality.

SI Tables S3−5 provide details for the income, city-size, and EPI tertile submodels. Figure 4 summarizes standardized coefficients for the urban form metrics for all of the submodels. We use the Monte Carlo subsample simulations from the CPS plot analyses to determine statistically significant changes in standardized coefficients for the submodels (n = 391−434): the blue shaded region in Figure 4 shows the fifth and 95th percentile range in $\beta \times$ IQR from the coefficient CPS plots in Figure 3 for a sample size of 400 (i.e., approximately one-third of the overall sample size, because these analyses divide the data set into tertiles). Figure 4 illustrates that contiguity may have a larger effect size for small cities and cities in countries with high environmental performance, and an attenuation of the contiguity - urban NO_2 relationship for large cities. Attenuation of the circularity - urban NO_2 relationship is exhibited for cities in countries with high income or high environmental performance. The impervious surfaces metric is sensitive to country-level income: cities in low-income countries exhibit a positive relationship between impervious surfaces and log-NO_2 (p = 0.11), whereas cities in high-income countries exhibit a significant negative relationship (p < 0.001). Aside from an increase in the effect for small cities, vegetation appears mostly unaffected by the factors considered here. Sensitivity models with interaction terms are presented in SI Tables S6−9. The effect modification from the interaction models strongly agree with most of our significant submodel findings (p < 0.001 for interaction terms), however, agreement is modest for the attenuation of circularity with increasing income and increasing EPI (p = 0.11 and 0.07 for income and EPI interaction terms, respectively) and the effect modification for population on

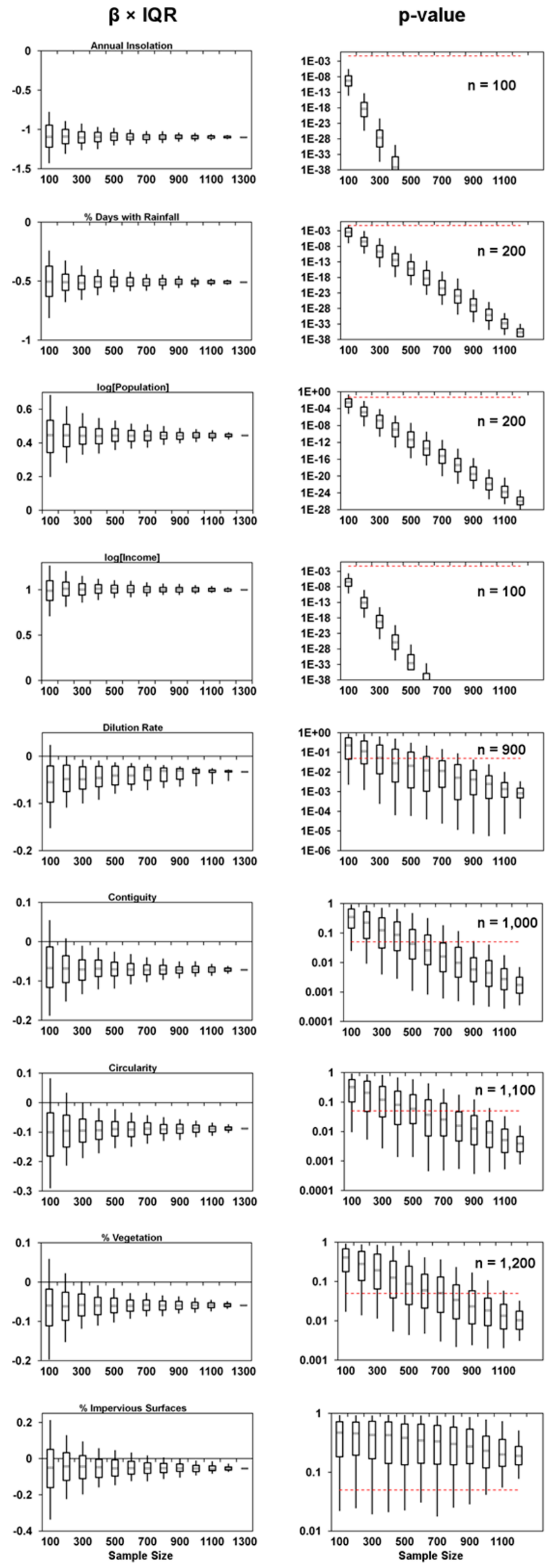

Figure 3. Summary of $\beta \times$ IQR (left) and p-value (right) for each variable based on Monte Carlo random sampling (500 iterations) for indicated subsample size. Boxes indicate 25th and 75th percentile values, lines indicate fifth and 95th percentile values, and bars indicates median values. For p-value plots, horizontal red-line indicates p = 0.05 value. For all panels except the bottom panel (impervious surfaces), the p-value decreases for larger sample sizes. Number in p-value plot (e.g., "n = 100" in top row) is an estimate of the minimum sample size for which the 95th percentile p-value is 0.05 or smaller.

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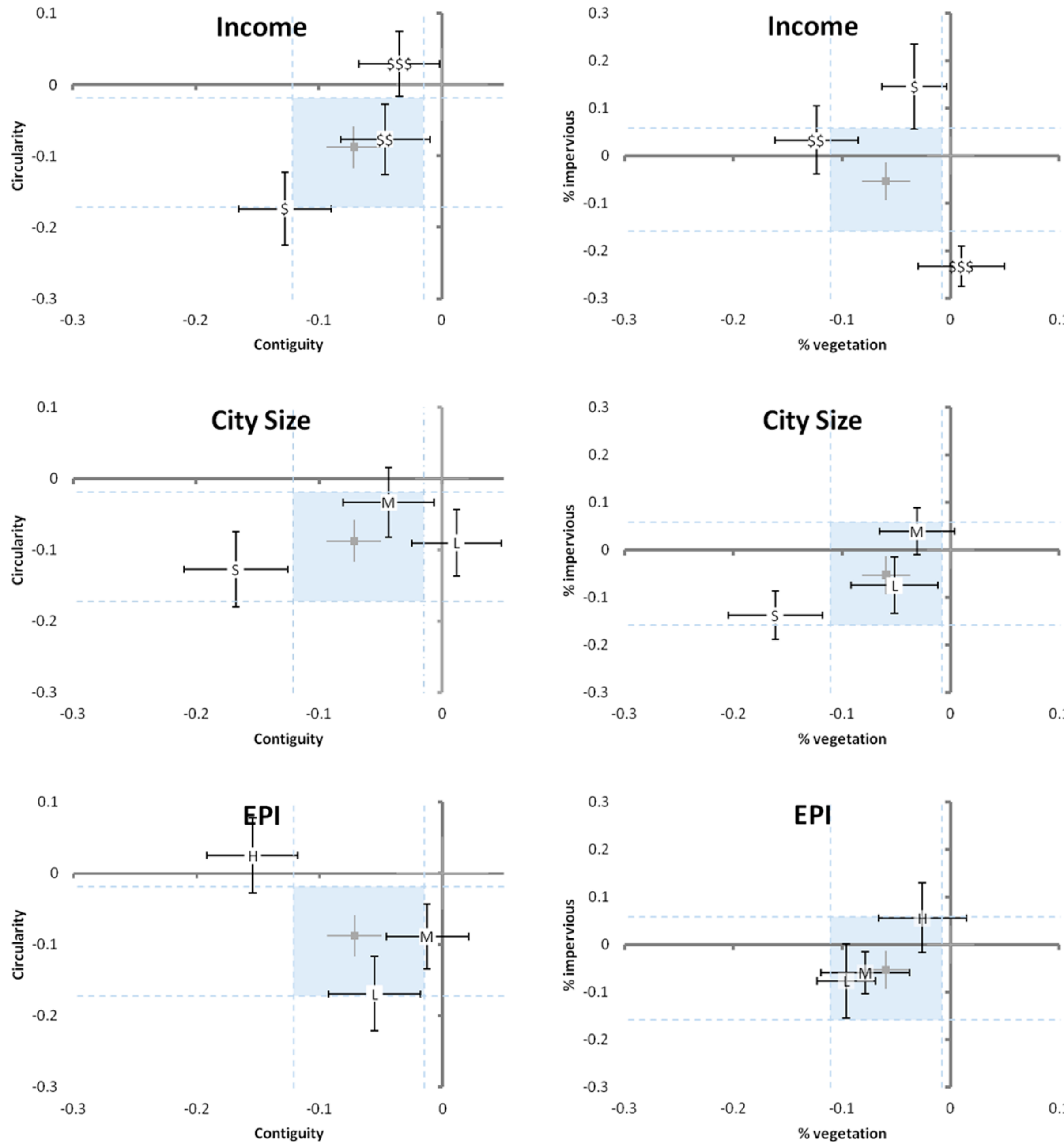

Figure 4. Summary of urban form coefficients for subsample models by tertile of income (top), city population (middle), and environmental performance index (bottom). Black symbols show $\beta \times$ IQR and lines indicate SE $\times$ IQR for the corresponding submodels, gray squares and lines show $\beta \times$ IQR and SE $\times$ IQR for the full model. Blue dashed lines show the 5th and 95th percentile values for $\beta \times$ IQR based on Monte Carlo random sampling at sample sizes approximating the tertiles (n = 400). Values outside of the blue shaded box are considered statistically significant (i.e., outside the 90% confidence interval of the value for the base model, based on the sample size of the tertile).

vegetation is the opposite direction of our submodel results (p = 0.15). Additionally, the interaction models illustrate a small, yet statistically significant, attenuation of vegetation with increasing income (p = 0.001) and increasing EPI ($p < 0.0001$).

Meteorology and country-level income play an important role in describing differences in urban NO_2 concentrations among cities; income, solar insolation, and precipitation together describe 52% of the variation in urban NO_2 concentration. Considering standardized coefficients, solar insolation and income have comparable effect sizes ($\beta \times$ IQR = −1.09 and 1.02 for insolation and log[income], respectively), and more than twice the effect size as the next largest predictors ($\beta \times$ IQR = −0.50 and 0.45 for precipitation and log[population], respectively). Of the three meteorological metrics, dilution rate has the smallest effect on concentrations ($\beta \times$ IQR = −0.03).

DISCUSSION

We find that three of the four urban form metrics considered in this study (contiguity, circularity and vegetation) have a statistically significant ($p < 0.008$) negative association with urban NO_2 concentrations, illustrating the potential for urban form to impact urban air pollution. The magnitude of the effect size of the three significant urban form metrics ($\beta \times$ IQR: −0.06 to −0.09) is similar to that of dilution, a consistent

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finding with previous work on this topic.[42] Despite the small effect size of these metrics, their combined effect could be large. In other words, if we hypothetically consider the results in Table 1 to be causal, a city that enhances their urban form may see improvement in urban air quality, or the offset of worsening air quality associated with population growth. For example, a city with circularity, contiguity and vegetation metrics at the 75th percentile could, on average, accommodate approximately twice the population of a city with these metrics at the 25th percentile while maintaining similar air quality. These findings illustrate the potential utility of urban form as part of a comprehensive strategy for addressing urban air pollution.

Subsample Models. Our subsample models, exploring changes in urban form metrics by income, city population size, and environmental performance tertiles, provide insight into factors that may alter the core urban form−urban NO_2 relationships. For low-income countries, increasing impervious surfaces is associated with worsened NO_2 air pollution, possibly indicating increased emissions from a higher level of developed land (or more specifically, car-centric developed land) within the built-up pixels defining a city. Impervious surfaces may also be capturing within-country differences in economic activity, and the resulting increase in emissions from those activities. On the other hand, for high-income countries the findings are seemingly counterintuitive: increasing impervious surfaces is associated with reduced NO_2 air pollution. One possible explanation is that in high income countries, the impervious surfaces metric is capturing differences in density (e.g., population, business), resulting in lower per capita VMT. As a sensitivity analyses we include logarithm of net population density (the total population divided by the total built-up area) as an explanatory variable, however, the population density coefficient is highly insignificant (p = 0.96) and does not change the other explanatory variable coefficients. It is possible that density characteristics not captured by net population density could be at play here, however, it is unclear. Interpretation of the impervious surfaces coefficient is complicated by the fact that it is associated with urban heat island effect, which could alter NO_2 concentrations in myriad ways (e.g., increased emissions from air conditioning usage, more NO_x as NO rather than NO_2, higher levels of daytime dilution owing to larger mixing area). Income also appears to impact the effect size of the circularity and vegetation metrics (cities in high-income countries exhibit an attenuation of the circularity and vegetation coefficients). These findings support further research on the differences in urban form - urban NO_2 relationships for cities in high- and low-income countries.

The magnitude of the contiguity coefficient appears to decrease with increasing city size: small cities exhibit a larger negative relationship with urban NO_2 compared to the full model, whereas in large cities contiguity appears to have no effect. A possible explanation for this finding is that, all else equal, a more contiguous city may have higher per-area NO_x emissions even if per capita emissions decrease because the emissions occur on a smaller footprint. In a larger city, this could result in higher concentrations for some parts of the city owing to (1) insufficient dilution relative to the increased local emissions, or (2) longer NO_x lifetime as a result of OH suppression from more spatially focused NO_x emissions. City size also impacts the magnitude of the vegetation parameter, with small cities exhibiting a larger vegetation coefficient. It is unclear why this would be the case, but the effect may arise from some convolution of vegetation's role as a depositional surface, and its role as a source of biogenic hydrocarbons that change the chemical regime for NO_2 oxidation. The fact that contiguity and vegetation both have larger impacts on urban NO_2 for small cities is an important finding, given that more than half of the global urban population live in smaller cities (<500 000 people).[1] The collective effect of the four urban form metrics is greater for smaller cities (combined $\beta \times$ IQR = −0.46, versus −0.22 for all cities), consistent with findings from Larkin et al. for East Asia[31] and further highlighting the importance of well-planned development and urban growth for smaller cities. This finding also highlights the need for further understanding of urban form and air pollution relationships in small urban areas; much of the current research has focused on large urban areas and megacities.

The magnitude of the circularity coefficient decreases with improved environmental performance, suggesting that circularity effects on urban NO_2 may be less important in countries with stronger environmental policy and performance. On the other hand, the magnitude of the contiguity coefficient is higher in countries with high environmental performance. These findings illustrate that environmental policy alters the relationship between urban form and air pollution, and suggests that the efficacy of urban form strategies may be dependent on existing environmental policies.[60]

Meteorology. Meteorological variables explain a large portion of the variability in urban NO_2 concentrations between cities. The effect size for precipitation is on par with that of population ($\beta \times$ IQR = −0.50 versus 0.45 for precipitation and log[population], respectively). Wet deposition is not a major sink for NO_2, so the large effect for precipitation seen here is somewhat surprising, however, it is consistent with published findings for urban NO_2 in East Asia.[31] Relative to solar insolation and precipitation, the effect size for dilution rate was small, possibly owing to the relatively short chemical lifetime of NO_2 in the atmosphere (daytime NO_x e-folding lifetimes estimated from airplane and satellite measurements for urban locations are ∼4−6 h[62,63]). It is also possible that the solar insolation and precipitation variables are in fact capturing other, correlating, aspects of meteorologically driven urban NO_2 variation; excluding them from the model results in a more than doubling of the dilution rate effect size ($\beta \times$ IQR = −0.08).

Limitations of the Study. A major limitation of our study is that it is cross-sectional, owing to the lack of built-up area estimates over time. That aspect hinders our ability to draw conclusions regarding causality. Our analysis is also limited by the characteristics of the data sets employed and their data quality. For example, the built-up area estimates include only cities with at least 100 000 people, yet many people live in (and much of the future growth of cities will be in) urban areas with fewer than 100 000 people. Similarly, our analysis excludes cities smaller than 50 km^2 because of the coarseness of the built-up area estimates and our need to avoid issues with calculating the contiguity index (see the Materials and Methods section). We cannot confidently extend claims from this analysis to cities below those thresholds (<100 000 people or 50 km^2). Another potential limitation of our analysis is our measure of urban air pollution: satellite-based NO_2 concentration. Measurements occur in the mid- to late morning, during satellite overpass, when NO_2 concentrations may be lower than 24-h average concentrations. We therefore may be underestimating concentrations for cities with large diurnal patterns that cannot be captured via this type of measurement.

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Environ. Sci. Technol. 2017, 51, 12707−12716

Another limitation of this study is that our air pollution metric employs ambient concentration rather than exposure. Urban form changes such as increased density may reduce net emissions and average concentrations, but exposures may be higher in dense neighborhoods and cities because sources and people are closer together.[64] For example, Schweitzer & Zhou employed a composite measure of regional compactness for U.S. Metropolitan Statistical Areas (i.e., Smart Growth America's sprawl index) and found that compact regions had lower concentrations of ozone, yet higher levels of exposure to ozone and fine particles (two important air pollutants).[26] In contrast, Clark et al. employed several regional urban form indicators for U.S. Urbanized Areas and found that while density was associated with higher ozone and fine particle exposure, another urban form metric (population-centrality) was associated with lower exposures.[28] Given the resolution of our air pollution data, we chose not to consider population exposure. It is potentially possible that increasing contiguity and compactness could worsen exposure, on average, despite our findings indicating improved ambient concentrations.

Implications of Findings. Overall, our findings demonstrate that urban form has a statistically significant relationship with urban NO_2 concentrations. Our cross-sectional investigation highlights the need for further study of urban design and planning as a potential strategy to address air quality. While meteorology (aside from dilution rate), country-level income, and city population size all had a larger effect on urban NO_2 than the urban form metrics, the combined impact of the three statistically significant metrics (contiguity, circularity, and vegetation) could have large consequences for concentrations. While these findings are generally consistent with our prior work, in this study we find that certain factors may alter the relationship between urban form and air pollution. For example, we find that urban form may have a greater impact on urban NO_2 for small cities than for large cities. This is an important finding given that more than half of the world's urban population lives in small urban areas, and because changes to urban form may be easier for small urban areas (owing to less existing infrastructure and the potential for greater relative impact from future growth). We also find that direction of effect for impervious surfaces differs between cities in high- and low-income countries, suggesting that urban form strategies may differ at various stages of growth and development.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.7b01194.

Tables S1−S9 (PDF)

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