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Investigating Links Among Urban Sprawl and Environmental Justice Indicators in US Territories

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Sprawl often characterizes unsustainable, car-dependent, and low-density urban development at the edges of cities. Much research has documented the relationship among sprawl and air pollutant concentrations and many studies have addressed sprawl's social implications, especially for low-income and minority groups. However, limited research has investigated the links between areas with increased levels of sprawl and air pollution, where vulnerable populations reside. This paper brings together the refined sprawl dataset from Smart Growth America and selected environmental justice indicators on air pollution-ozone and air toxics-from the US Environmental Protection Agency's Environmental Justice Screening and Mapping Tool (EJSCREEN), in a national-level analysis of U.S. territories. Through Pearson correlations and a series of logistic regressions, the significant connection of sprawl and ozone concentrations is shown, in areas with more low-income, and less educated groups with higher percentages of children. On the other hand, while air toxics cancer risk is higher in areas with low-income, and linguistically isolated racial minorities, it has lower levels in more sprawled areas. Upon a closer look, it is shown that only selected dimensions of compactness link to higher cancer risk, while aspects such as a higher mix of jobs may have a reverse effect on it. These findings provide new directions in the ongoing discussion of sustainable urban development patterns and suggest that the focus should be on development that can promote better air quality, while simultaneously reducing social vulnerability to environmental challenges, with additional benefits for local innovation and community building.

Keywords: Sprawl, Environmental Justice, Air Pollution, Vulnerable Populations, Urban Form

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Introduction

Sprawl usually describes an urban development pattern that is inefficient in its use of land (Freilich *et al*., 2010). It is generally negatively charged and commonly associated with 'low density development on the edges of cities and towns that is poorly planned, land-consumptive, automobile dependent and designed without regard to its surroundings' (Beck, Kolankiewicz and Camarota, 2003). Initially, some of the driving forces behind sprawling expansion included housing affordability, access to open space, proximity to nature and a better climate and air quality (Bruegmann, 2006; Gavrilidis et al., 2019). Instead, sprawl in the US has been connected to numerous social and environmental impacts, including weakening of social capital through inner-city decline, racial segregation, lack of affordable housing, deterioration of existing built-up areas, global warming through increased traffic volume, and erosion of agricultural land and open space (Burchell et al., 1998; Camagni et al., 2002; Freilich et al., 2010; Kahn, 2001; Wilson and Chakraborty, 2013).

This paper explores the spatial linkages between sprawl and environmental injustice indicators in the US. Specifically, it examines whether socially vulnerable groups reside in areas with poor air quality -ozone concentrations and cancer risk from air toxics- and high levels of sprawl, to characterize potential synergies of sprawl and air pollution on certain areas and populations. The following sections briefly discuss sprawl and environmental justice metrics and provide a review of past research and current knowledge gaps on the simultaneous relationship between urban development patterns, air quality and socially vulnerable populations, and implications for environmental injustice.

Sprawl Metrics and Links to Air Pollution

Several studies have documented sprawl's possible causes and consequences (see Galster et al., 2001; Wei and Ewing, 2018), yet, there is widespread disagreement about what exactly constitutes sprawl and how to quantify it (Christiansen and Loftsgarden, 2011; Jaeger et al., 2010). The famous expression that 'most people would be hard pressed to define urban sprawl, but they know it when they see it' (Ewing, et.al, 2002), vividly describes the associated uncertainty and ongoing debates about sprawl. Numerous attempts have been made to suggest a widely accepted working definition and subsequently, measures and indexes to inform practice, but there are still those who support that more research is needed, as sprawl's determinants and characteristics 'are not yet fully understood' (Torrens and Alberti, 2000).

Perhaps the most popular variables used to quantify sprawl are density of housing, population and employment, land use mix and level of dependence on automobile travel (Zhao and Kaestner, 2010), but issues with scale arise. Torrens and Alberti (2000) highlight that measurements of sprawl may look different in a neighborhood, block, city county or metropolitan area. Eid *et al*. (2007) point out to the inability of county-level measurements in capturing the 'neighborhood self-selection.' Lastly, Gordon and Richardson (1997) question whether the total area of a place should be included in the calculations versus the area upon which people would normally reside (excluding water bodies, wetlands etc.).

Among the most famous past attempts to operationalize sprawl is an index developed by USA Today (El Nasser and Overberg, 2001) , related to population living in urbanized areas and change in this population between 1990 and 1999. Surprisingly, this study characterized Los Angeles – a typical sprawling example- less sprawling than New York. Similarly, the Sierra Club (1998) quantifies sprawl based on population shifts from city to suburb, land area growth vs. population growth, time spent in traffic, and loss of open space (Sierra Club, 1998).

In 2002, Smart Growth America (SGA) and the US Environmental Protection Agency (EPA) published a study that proposed a sprawl index based on two major dimensions: development density and street accessibility for 448 metropolitan counties in the US (Ewing and Hamidi, 2014). The study findings were updated in 2014 to include 993 counties and additional built-environment dimensions: residential and employment density, neighborhood mix of homes, jobs and services, strength of activity centers and downtowns and street accessibility, which were all combined into one sprawl index (Ewing and Hamidi, 2014). The refined index incorporates a large US segment, relatively recent census data and addresses sprawl through a variety of built environment dimensions, which together cover the most popular definitions of urban sprawl.

Since its first release, this index has been used in several studies and has been linked to physical inactivity, obesity, traffic fatalities and others. A considerable amount of literature utilizes the 2002 version of the SGA index and focuses on the environmental impacts of sprawl, specifically its links to air pollution. Stone (2008) found significant associations among 45 sprawled regions in the US and high ozone exceedances. Similarly, Schweitzer and Zhou (2010) linked neighborhood-level air pollution (ozone and particulate matter) and sprawl in 80 US areas. The authors also highlighted higher exposures in neighborhoods with poor households and racial minorities. Lastly, Bereitschaft and Debbage (2013) explored 86 US areas and related sprawl-like urban morphologies with higher concentrations and emissions of air pollution and carbon dioxide.

The links between urban sprawl and air pollution have also been investigated in other countries, beyond the US. Kang et al., (2019) examined ozone pollution and urban form in Korea and found that land use mix, clustering and development concentration were significantly associated with better air quality. Somewhat contradicting findings come from Li and Zhou (2019), who did a large-scale analysis of 288 Chinese cities and linked 5 metrics of urban form with 6 air pollutants. Their results suggested that lower-sized, moderately scattered, polycentric cities may be preferred for better air quality. However, not all scattered development is considered sprawl, but only the type of 'uncoordinated growth' without concern for its consequences (Batty et al., 2003). The above indicate that while there are documented linkages between some sprawl dimensions and certain air pollutants, there is limited understanding on the connection of types of urban expansion and combined socio-environmental inequalities.

The Relationship of Sprawl and Environmental Justice

As seen previously, urban sprawl is one of the most pressing concerns facing American cities. There is a lot of debate on how to measure it and ongoing research continuously addresses its environmental consequences and attempts to find remedies that promote more sustainable and healthier urban development patterns. There is rich literature on the relationship between sprawled areas and air quality, but demographic indicators are usually absent from such studies, even though much environmental justice-oriented studies highlight the disproportionate burdens of outdoor pollutant concentrations on socially vulnerable populations. For instance, Morello-Frosch and Jesdale (2005) examined links between socioeconomic status (SES) and ambient air toxics exposures and their associated cancer risks for 309 metropolitan areas in the US and found that racial residential segregation highly affects the degree of such exposure. Likewise, Pastor et al. (2005) examined the spatial distribution of environmental risk in the state of California and their results showed a persistent disproportionate exposure of ambient air toxics by race. More recently, Tessum et al. (2019) formally quantified unequal burdens from air pollution to black and Hispanic minorities in the US, through their 'pollution inequity' metric.

The concept of environmental justice (EJ) means both a social movement that fights for the just distribution of environmental costs and benefits, and an environmental movement that brings together theories of the environment regarding sustainability, law, policy, planning and ecology (Schlosberg, 2009). As such, it incorporates a clear spatial component where spatial forms and scales connect to socio-environmental disparities (Walker, 2009). Environmental justice critiques have often targeted traditional planning issues, among which are smart growth and sprawl (Agyeman, 2007). However, to date, limited, if none, research has examined directly the socio-environmental implications of urban form characteristics.

Revealing issues with environmental injustice heavily depends on the way EJ is measured and analyzed in a spatial context. Typically, variables combine environmental stressors with sociodemographic characteristics and there is increasing interest in developing tools that can capture cumulative socio-environmental disparities at the most local scales (Sadd et al., 2011). Ongoing work on producing EJ metrics is carried out by several U.S. governmental entities and non-profit organizations, such as the Environmental Protection Agency (EPA), the Department of Health and Human Services, the National Institute of Health, the National Library of Medicine and the Environmental Working Group, most of which are continuously developed and updated (Amiri and Zhao, 2019). A relatively simple and popular tool is EJSCREEN, a mapping and data reporting tool by EPA that links environmental and demographic indicators in the US, in the form of EJ indexes (EPA, 2016). EJSCREEN contains data on environmental stressors related to air, dust, waste and water pollution and data on demographic indicators, mainly related to income, race, education level, and age. These indicators are calculated at the block-level and can be summarized within a defined buffer area. As noted in the relevant EPA report, EJSCREEN is not suitable for characterizing a site as EJ or non EJ community, as it is difficult to capture all environmental concerns at the same time; it is rather designed for screening purposes, meaning to provide an overview and identify areas in need for additional considerations (EPA, 2016).

To date, EJSCREEN has been used in several studies, including assessing the performance of and validating newly developed EJ tools (see Driver et al., 2019; Grier, Mayor and Zeuner, 2019; Rowangould et al., 2019), linking high levels of outdoor pollution and low access to jobs (see Zhao, Gladson and Cromar,2018), identifying the socio-environmental characteristics of renewable energy manufacturing sites (see Harris, 2018), and associating adverse pregnancy rates with air pollution in low-income and minority sites (see Cifuentes et al., 2019). Yet, there is no literature utilizing the EJSCREEN data to bridge environmental justice and built environment characteristics.

Perhaps one of the few EJ-oriented studies that links to urban development is this of Pratt et al. (2015). The authors co-examined SES status and risks from traffic density and related air pollutants in Minnesota, USA and found higher than the mean exposures for residents of lower SES status. They further identified that residents living outside the urban core had lower risks of exposure but drove more, while those closer to the urban core tended to drive less and had higher exposures. On a related note, Woo et al. (2019) showed environmental inequities for racial and ethnic minorities through exposure to 3 types of air pollution in the US and further concluded that this exposure was higher in metropolitan areas with higher levels of residential segregation. These studies indicate that there is increasing interest from EJ-oriented research to establish connections among urban form, air quality and demographic characteristics.

Research Items

The question of the relationship between different patterns of urban form and their environmental and social costs has been increasingly investigated from urban scholars, especially as governmental commitments to urban sustainability accelerate (Camagni et al., 2002). Evident in the above is that sprawl, air pollution and social vulnerability are three phenomena with many interlinkages (Agyeman, 2007), but with multiple dimensions, which are often challenging to fully capture in single-metric and large-scale approaches. In simplified terms, sprawl translates to increased air pollution through higher traffic volumes from the dependency on cars (Burchell et al., 1998; Johnson, 2001), and, in turn, air pollution is higher in areas with residents of a lower SES status. Similarly, sprawl may promote social isolation, through racial and income segregation, e.g. through the uneven distribution of public services and transport infrastructure (Zhao, 2013), with persistent air quality problems and higher exposures in the most isolated communities. Therefore, although difficult to measure directly in physically meaningful units, it is logical to assume that there may be a simultaneous connection between sprawl, air pollution and socially vulnerable populations, in need for further investigation.

This paper contributes findings on research items that have partially been examined by some of the studies reviewed in the previous paragraphs. The central research question asks whether sprawl contributes to increased air pollution in US areas with socially vulnerable population groups. Connections among some sprawl dimensions and selected air pollutant indicators, such as ozone, have been covered previously, as well as connections among other indicators, such as air toxics cancer risk, and racial and income minorities. But the risk from air toxics and sprawl has not been examined, neither is the simultaneous relationship among sprawl, air pollution-ozone and air toxics cancer risk- and locations with higher percentages of low-education, low-income, isolated, racial minorities of seniors and children, which is the focus of this work.

Methods

Research linking directly urban form and environmental injustice is still in embryonic stages. Existing studies with data-and-modeling-driven agendas mostly adopt cross-sectional approaches, where they examine sprawl and air quality, or sprawl and social discrimination. They further limit their analysis in narrow individual groups and in bounded spatial contexts. In this work, a cross-sectional, national-level analysis is carried out, based on a mixed sample of environmental and sprawl indicators, while controlling for demographic variables targeting vulnerable populations. The next sections describe this process in more detail.

Data Collection

Sprawl and environmental justice data were taken from the previously described SGA index and EJSCREEN databases respectively. More descriptions are given below.

Sprawl Data

County-level estimates of sprawl in the United States were published in 2014 from Smart Growth America and were taken from the National Cancer Institute (NIH), Center for Geographic Information Systems and Science for Cancer Control website[1]. The data are

[1] Sprawl datasets and descriptions can be found at the NIH, GIS and SCC website (https://gis.cancer.gov/tools/urban-sprawl/).

available for 993 US counties; each county corresponds to a row in the sprawl dataset and is assigned the state it belongs, a density factor, a mix factor, a centering factor and a street factor, as well as a composite index, as of 2010. Specifically, the density factor indicates development density, the mix factor refers to land use diversity, the centering factor represents street accessibility, and the composite index combines them all together. The four factors were produced through principal component analysis and were then summed, giving each dimension of sprawl equal weight in the composite index (Ewing and Hamidi, 2014).

Environmental Justice Data

Environmental justice data were taken from the US Environmental Protection Agency (EPA) website[2]. They are part of the Environmental Justice Screening and Mapping Tool (EJSCREEN) and exist either in comma-separated files or in the form of geodatabases. They combine block-level environmental and demographic indicators as of 2016.

The environmental indicators are direct or proxy estimates of potential exposure to environmental pollutants and were selected based on their public health significance, relevance to environmental justice, highest resolution possible and coverage (EPA, 2016). Specifically, they include variables related to air (air toxics cancer risk, respiratory hazard index, diesel PM, particulate matter, ozone, traffic proximity and volume), dust and lead paint (lead paint indicator), and waste/water (proximity to risk management plan (RMP) sites, proximity to treatment storage and disposal facilities (TSDFs), proximity to national priorities list (NPL) sites, and proximity to major direct water dischargers).

The demographic indicators are general estimates of a community's potential susceptibility to environmental pollution. For example, individuals may be more vulnerable when they are of very young or older age, have poor health, have reduced access to care, and lack resources, language skills or education (EPA, 2016, Cohen and Martinez, 2011). They are in a household basis and include percent low-income (income less than or equal to twice the federal 'poverty level'[3]), percent minority (race other than white-alone[4]), percent with less than high school education for people of age 25 and older, percent linguistic isolation (people living in linguistically isolated households[5]), percent under age 5, and percent over age 64.
As noted in the associated EJSCREEN documentation, there is a trade-off between resolution and precision; the data do not necessarily provide the full picture of a location's pollution exposure but are rather suitable to identify areas for further review (EPA, 2016).

Data Analysis

The data analysis in this paper examines the relationship between selected environmental indicators and sprawl in US territories, while controlling for several demographic estimates. The central hypothesis is that areas with vulnerable population groups and higher levels of environmental pollution, may also be associated with higher levels of sprawl. The sprawl and environmental justice datasets described above, were utilized to perform a series of block-level, logistic regression analyses in Stata. The environmental variables of focus are ozone

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[2] Environmental Justice datasets and descriptions can be found at the US EPA website (https://www.epa.gov/ejscreen/download-ejscreen-data).
[3] More information about the Federal Poverty Level (FPL) can be found at: https://www.census.gov/topics/income-poverty/poverty/about/glossary.html#par_textimage_25.
[4] Minority is defined based on: https://factfinder.census.gov/help/en/race.htm.
[5] A household in which all members aged 14 years and over speak a non-English language and also speak English less than "very well" (have difficulty with English) is considered linguistically isolated (EPA, 2016).

and air toxics cancer risk (air pollution related), as they are the most visible indicators in a block-level investigation and are entered as dependent variables. Then, sprawl is the policy independent variable that is represented by the composite index described previously, and combines the four factors of density, mix, centering and street. Lastly, all six demographic indicators of low income, minority, lower education, linguistic isolation, children and elderly are entered as additional control variables in the analysis.

Regression analysis is often used in studies examining the relationship between sprawl and environmental indicators, and ozone is a frequently investigated pollutant (see Bereitschaft and Debbage, 2013; Kang et al., 2019; Li and Zhou, 2019; Schweitzer and Zhou, 2010; Stone, 2008). However, this is not the case with the air toxics cancer risk. In addition, while several studies address the unequal burden of outdoor pollutant concentrations on socially vulnerable populations (see Morello-Frosch and Jesdale, 2005; Pastor *et al*., 2005; Pratt *et al*., 2015; Tessum *et al*., 2019; Woo et al., 2019), related demographic indicators are not usually present in existing statistical models of sprawl and air pollution. Likewise, many researchers have linked selected sprawl dimensions with socio-demographic indicators, such as income or racial segregation (see Guo *et al*., 2019; Nguyen, 2010), but have not included the intermediate connection between environmental and demographic variables.

After data acquisition, sprawl, environmental and demographic variables described previously were merged into one dataset in MATLAB[6], based on each county's unique identification number (FIPS)[7]. Necessary clean-up processes took place, such as identification of extreme/wrong values, deletion of missing values, and generation of fixed effects to account for spatial autocorrelation (Berrigan *et al*., 2014). Block information is essentially nested within counties and therefore, shares the counties' physical characteristics. Fixed effects for places take care of this spatial autocorrelation and counties were classified as northeast, northwest, south and west, where south is the base category[8].

During the aggregation process, there was an information loss, either because the environmental justice data did not cover all areas contained in the sprawl dataset, or reversely. Therefore, the resulting dataset has information for 168,607 blocks on the variables shown in Table 1.

Both environmental indicators (ozone and ATCR) were turned into binary variables in this analysis. Specifically, existing air quality indexes often treat ozone as a categorical variable with values less than 50 parts per billion (ppb) indicating good air quality levels, and values above 50 ppb indicating avoidance of outdoor exposure, especially for vulnerable population groups such as children and seniors (EPA, 2015a). Here, the interest is limited in safe versus non-safe air quality levels. Therefore, a new ozone variable was generated, where the value of 1 was assigned to places with ozone>50 ppb, and 0 otherwise. Similarly, a new air toxics cancer risk variable was created, with values less than 45 in a million, expressing low risk, and values above this threshold indicating increased cancer risks for the study areas (1 was assigned to places with ATCR>45, and 0 otherwise). Table 2 summarizes the average, minimum and maximum values for the variables in the sample.

[6] MATLAB is a programming platform. More information can be found at: https://www.mathworks.com/discovery/what-is-matlab.html.
[7] More information about FIPS can be found at: https://www.census.gov/geographies/reference-files/2016/demo/popest/2016-fips.html.
[8] Classifications of the US states are based on a suggested classification system from the US Census Bureau.

Table 1: *Variables in the Sample.*

Group	Variable	Type	Description
Environmental	Ozone	Binary	Summer seasonal average of daily maximum 8-hour concentration in air, in parts per billion (ppb) (EPA, https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen).
	Air Toxics Cancer Risk (ATCR)	Binary	Probability that individuals of a place will develop cancer from inhalation of air toxics (carcinogens in ambient outdoor air) (EPA, https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen).
Sprawl	Composite index	Continuous	A county’s sprawl/compactness score. Higher values indicate less sprawl and more compactness (if >100 indicates less sprawl) (Ewing and Hamidi, 2014).
	Density Factor	Continuous	Combines population density and urban density with built land (Ewing and Hamidi, 2014).
	Mix Factor	Continuous	Combines balance of jobs to total population and the mix of job types (Ewing and Hamidi, 2014).
	Centering Factor	Continuous	Expresses the proportion of people and businesses located near each other in different block groups (Ewing and Hamidi, 2014).
	Street Factor	Continuous	Combines the length of street block, the block size, the percent of blocks that are urban in size, the density of street intersections and the street connectivity (Ewing and Hamidi, 2014).
Demographics	Percent low income	Continuous	
	Percent minority	Continuous	
	Percent < high school	Continuous	
	Percent linguistic isolation	Continuous	
	Percent < 5	Continuous	
	Percent > 64	Continuous	

Table 2: *Summary Statistics for the Sample's Variables.*

Variable	Mean	St. Deviation	Min	Max
Ozone	47.61	7.76	0	73.76
Air toxics cancer risk	42.07	12.20	0	826.31
% Low-income	0.34	0.22	0	1
% Minority	0.39	0.31	0	1
% < High-school	0.14	0.13	0	1
% Linguistic isolation	0.05	0.09	0	1
% < 5	0.06	0.04	0	1
% > 64	0.14	0.09	0	1
Composite index	125.61	40.00	45.49	425.15
Density factor	121.64	61.01	88.03	654.01
Mix factor	120.60	18.82	22.76	177.53
Centering factor	116.91	35.66	66.08	400.25
Street factor	121.92	32.99	40.96	230.33

Results

Tables 3 and 4 report correlations between the environmental indicators, the composite index and the demographic estimates. In the case of ozone, correlations are particularly weak; the strongest correlations are those of the index, percent linguistic isolation and percent minority. Based on its sign, as the composite index goes up (meaning higher density and less sprawl), it is less likely that the outdoor ozone will be high (>50 ppb), and the same counts for percent linguistic isolation and percent minority.

In the case of Air Toxics Cancer Risk (ATCR), correlations are somewhat stronger, and the signs are reverse; the highest correlations are those of percent minority, the index, percent low income and percent with less than high school diploma. Now, as the composite index, hence urban density, goes up, so does the probability of air toxics cancer risk and the same counts for all the demographic indicators, except from percent seniors.

The results of the logistic regression models are presented in Tables 5 - 10. The objective is to examine whether environmental indicators are associated with urban sprawl and related demographics. For each environmental indicator, four regression models are tested, beginning with models using only the composite index, and progressively adding demographic indicators and fixed effects for states.

Table 3: *Pearson's Correlation Matrix for Ozone.*

	Ozone	Index	Minority	Low Income	<High School	Linguistic Isolation	<5	>64	State
Ozone	1.00								
Index	-0.17	1.00							
Minority	-0.09	0.29	1.00						
Low Income	0.01	0.03	0.55	1.00					
<High School	-0.03	0.08	0.60	0.67	1.00				
Linguistic Isolation	-0.10	0.25	0.50	0.38	0.57	1.00			
<5	0.03	0.00	0.26	0.29	0.23	0.17	1.00		
>64	-0.03	-0.06	-0.29	-0.19	-0.15	-0.14	-0.33	1.00	
State	0.14	-0.20	0.17	0.08	0.10	0.07	0.05	-0.04	1.00

***Table 4:** Pearson's Correlation Matrix for Air Toxics Cancer Risk.*

	ATCR	Index	Minority	Low Income	<High School	Linguistic Isolation	<5	>64	State
ATCR	1.00								
Index	0.31	1.00							
Minority	0.32	0.29	1.00						
Low Income	0.20	0.03	0.55	1.00					
<High School	0.18	0.08	0.60	0.67	1.00				
Linguistic Isolation	0.19	0.25	0.50	0.38	0.57	1.00			
<5	0.07	0.00	0.26	0.29	0.23	0.17	1.00		
>64	-0.12	-0.06	-0.29	-0.19	-0.15	-0.14	-0.33	1.00	
State	0.08	-0.20	0.17	0.08	0.10	0.07	0.05	-0.04	1.00

***Table 5:** Logistic Regression Results for Ozone. * Statistically Significant at the 0.05 Level.*

	M1	M2	M3	M4
Index	0.988*	0.990*		0.988*
	(0.000)	(0.000)		(0.000)
Minority		0.704*	0.515*	0.822*
		(0.016)	(0.012)	(0.021)
Low Income		1.593*	1.434*	1.219*
		(0.050)	(0.047)	(0.041)
< High School		1.210*	2.287*	1.478*
		(0.073)	(0.143)	(0.094)
Linguistic Isolation		0.162*	0.085*	0.158*
		(0.012)	(0.006)	(0.013)
<5		3.954*	4.250*	3.031*
		(0.525)	(0.591)	(0.426)
>64		0.356*	0.464*	0.495*
		(0.020)	(0.027)	(0.029)
Northeast			0.411*	0.544*
			(0.007)	(0.010)
Midwest			3.252*	3.807*
			(0.045)	(0.055)
West			2.433*	2.782*
			(0.033)	(0.039)
Intercept	2.972*	2.514*	0.558*	1.799*
	(0.066)	(0.068)	(0.010)	(0.057)
Pseudo R^2	0.025	0.032	0.1019	0.113
LR x^2	5,659	7,271	23,220	25,752
N	168,607	168,607	168,607	168,607

In all models of Table 5, the composite index is statistically significant at the 0.05 level. It is also negatively related to ozone as expected, therefore, as the density of a block increases, it is more likely that ozone levels among its residents will be lower. We also see that as more variables are added, the index coefficient increases slightly, probably because of omitted variables bias in the previous models.

The assessment of model fit that follows, focuses on the full logistic model 4 that includes the composite index, demographics and fixed effects. Specifically, the LR x^2 indicates a better model fit with a value of 25,752, at 10 degrees of freedom with p-values of 0.000. Therefore, the null hypothesis can be rejected, and it can be concluded that the model is statistically significant. Lastly, the correctly and incorrectly predicted results of the model are checked through running specificity and sensitivity tests, shown in Table 6. Based on the results of the test, a 69.67% of the model is correctly specified.

Table 6: *Results of Specificity and Sensitivity tests for Ozone.*

	True		
Classified	D	-D	Total
+	38465	20899	59364
_	30243	79000	109243
Total	68708	99899	168607
Correctly Classified		69.67%	

Evident in Table 5 is the statistically significant effect, but relatively low magnitude, of sprawl on ozone concentrations; as sprawl increases, ozone levels increase, which indicates that more compact urban forms may be preferred over sprawled areas for improved ozone levels. The same happens with lower income areas with less educated population that have higher magnitudes, where we see hints of environmental discrimination; ozone levels go up for low income communities with less access to education. This pattern is also alarming as ozone levels appear increased in areas with higher percentages of children under 5. Lastly, possibly the most surprising findings relate to senior, minority and linguistically isolated communities, where ozone concentrations are lower.

The next table zooms into the four sprawl factors and their relationship with ozone concentrations. The first model includes the whole sample, while the next models only include subsets with vulnerable populations.

As shown in Table 7, in areas with lower street and density factors, ozone concentrations go up, while the opposite is true for mix and centering factors. The same pattern continues for subsets of the sample with vulnerable populations; if we only include those blocks with low income groups of 40% or more, and blocks with 20% or more people with less than high school education, density and street factors go up with lower ozone levels. Several other thresholds were tried in the analysis (e.g. 50%) and the directions of the coefficients remain the same, while the magnitudes get slightly higher.

In all models of Table 8, the composite index is statistically significant at the 0.05 level. The composite index is positively associated with the air toxics cancer risk, therefore, as the density of a block increases, it is more likely that the air toxic cancer levels among its residents will be higher. Same as with the case of ozone, as more variables are added, the index coefficient increases slightly, assuming omitted variables bias in the previous models.

Table 7: *Logistic Regression Results for Ozone and Sprawl. *Statistically Significant at the 0.05 Level.*

	All Sample	Low Inc> 40%	<High>20%
	M1	**M2**	**M3**
Density Factor	0.982*	0.976*	0.976*
	(0.000)	(0.000)	(0.000)
Mix Factor	1.011*	1.024*	1.027*
	(0.000)	(0.000)	(0.000)
Centering Factor	1.003*	1.006*	1.010*
	(0.000)	(0.000)	(0.000)
Street Factor	0.995*	0.990*	0.985*
	(0.000)	(0.000)	(0.000)
Intercept	1.590*	0.890*	0.699*
	(0.059)	(0.056)	(0.054)
Pseudo R^2	0.04	0.065	0.087
LR x^2	9,393	5,589	4,842
N	168,607	62,658	41,705

Table 8: *Logistic Regression Results for Air Toxics Cancer Risk. * Statistically Significant at the 0.05 Level.*

	M1	M2	M3	M4
Index	1.023*	1.019*		1.026*
	(0.000)	(0.000)		(0.000)
Minority		3.362*	5.420*	2.032*
		(0.081)	(0.125)	(0.052)
Low Income		2.630*	2.576*	4.088*
		(0.088)	(0.086)	(0.144)
< High		0.812*	0.312*	0.816*
		(0.051)	(0.019)	(0.052)
Linguistic Isolation		0.853*	2.551*	0.474*
		(0.063)	(0.185)	(0.078)
<5		0.468*	0.253*	0.615*
		(0.066)	(0.035)	(0.090)
>64		0.316*	0.265*	0.216*
		(0.020)	(0.016)	(0.014)
Northeast			1.043*	0.481*
			(0.015)	(0.008)
Midwest			0.271*	0.172*
			(0.004)	(0.003)
West			0.841*	0.630*
			(0.011)	(0.009)
Intercept	0.031*	0.029*	0.405*	0.026*
	(0.026)	(0.000)	(0.007)	(0.000)
Pseudo R^2	0.086	0.129	0.114	0.179
LR x^2	19,242	28,938	25,501	39,749
N	168,607	168,607	168,607	168,607

The assessment of model fit that follows, focuses on the full logistic model 4 that includes the composite index, demographics and fixed effects. Specifically, the LR x^2 indicates a better model fit with a value of 39,749, at 10 degrees of freedom with p-values of 0.000. Therefore, the null hypothesis can be rejected, and it can be concluded that the model is statistically significant. Lastly, the correctly and incorrectly predicted results of the model are checked through running specificity and sensitivity tests, shown in Table 9. Based on the results of the test, a 71.93% of the model is correctly specified.

Table 9: *Results of Specificity and Sensitivity tests for Air Toxics Cancer Risk.*

Air Toxics Cancer Risk			
	True		
Classified	D	-D	Total
+	29952	14402	44354
_	32926	91327	124253
Total	62878	105729	168607
Correctly Classified		71.93%	

The case of air toxics cancer risk is different than that of ozone, where as sprawl goes down, so does the cancer risk from air toxics, although the magnitude is again relatively small. This indicates that further investigation may be needed to understand this relationship. The highest magnitudes are those of senior, low income areas located in midwest states, followed by minority and linguistically isolated places in the northeast. Low education, minority percent and percent of children under 5 also have significance but again, much lower effect over the environmental indicator. In terms of signs, minority and low-income areas are indeed more susceptible to higher air toxics cancer risk, highlighting disproportionate environmental burdens. But this finding does not apply to senior, linguistically isolated areas with less access to education, or places with children under 5.

Table 10: *Logistic Regression Results for Air Toxics Cancer Risk and Sprawl. * Statistically Significant at the 0.05 Level.*

	All Sample	**Low Inc> 40%**	**Minority>40%**
	M1	**M2**	**M3**
Density Factor	1.021*	1.002*	1.026*
	(0.000)	(0.000)	(0.000)
Mix Factor	0.995*	1.001*	0.993*
	(0.000)	(0.000)	(0.000)
Centering Factor	1.005*	1.004*	1.002*
	(0.000)	(0.000)	(0.000)
Street Factor	1.002*	0.994*	0.989*
	(0.000)	(0.000)	(0.000)
Intercept	0.030*	0.045*	0.267*
	(0.001)	(0.002)	(0.018)
Pseudo R^2	0.095	0.084	0.078
LR x^2	21,311	7,329	7,580
N	168,607	62,658	69,725

Same as before, Table 10 zooms into the four sprawl factors and their relationship with air toxics cancer risk. The first model shows the results of the whole sample, while the next models focus on subsets of vulnerable groups.

Table 10 shows that as sprawl dimensions increase (less compactness and more sprawl), cancer risk from air toxics goes down, except for the mix factor. Areas with a higher mix factor are likely to have lower air toxics cancer risk. The pattern changes in areas with low-income population of more than 40%, whereas density, mix and centering factors go up, ATCR increases, except from the street factor. Lastly, in areas with racial minorities of more than 40%, the cancer risk from air toxics goes up with higher density and centering factor but goes down when mix and street factors go up.

Discussion

The results from the analysis shown in Tables 5 – 10 revealed statistically significant links between urban sprawl and environmental justice in US territories. There are two main findings that emerge from this work:

Degrees of sprawl contribute to the 'ozone paradox': The results from the logistic regression of Table 5 confirm the central hypothesis and validate existing findings that in more sprawled places in the US, residents may have a higher risk of being exposed to ozone concentrations. This finding aligns with previous studies that support an association between ozone and less, compact urban form that may lead to higher traffic volume, which may be lower in higher density developments due to the availability of public transportation (Schweitzer and Zhou, 2010; Stone, 2008; Stone and Rodgers, 2001). In addition, it was shown that ozone concentrations are indeed associated with higher levels of low-income and less than high school education, which has also been shown elsewhere (see Schweitzer & Zhou, 2010). Lastly, Table 7 shows a weak, but statistically significant, association between ozone concentrations in places with more than 40% low-income and low educational levels, and some sprawl dimensions -density and street factors-, which has not been previously investigated. This last finding is the first, preliminary attempt to directly connect sprawl and environmental injustice.

Some dimensions of sprawl contribute to higher air toxics cancer risk, while others reduce it: Based on Table 8, it is shown that as compactness levels go down, so does the risk from being exposed to carcinogenic air toxics. Again, this association is statistically significant, but has a small magnitude. While there exists no research directly addressing this relationship, human exposure to outdoor air pollutants that may cause cancer is a very important variable that should be part of human-centric approaches linking sprawl with air pollution. Moving forward, the next interesting finding from Table 8 shows that ATCR is higher in areas with higher percentages of racial minorities, low-income and linguistically isolated groups. It overlaps with ozone in the low-income variable and confirms the asymmetrically distributed burdens of environmental pollution that have been shown elsewhere (see Pratt et al., 2015; Schweitzer and Zhou, 2010; Tessum et al., 2019; Woo *et al*., 2019). Lastly, Table 10 reveals statistically significant, but weak, associations between higher density and centering factors and higher levels of ATCR in blocks with minorities of more than 40%, but lower cancer risk for a higher mix factor. Along with the findings from Table 8, it does not indicate that sprawl is good; instead, it raises the question of how much compactness and less sprawling is good, and which dimensions we should be focusing on for future development.

Limitations

A statistical analysis of the links between urban form, air pollution and vulnerable populations is definitely complicated, as it attempts to connect multi-dimensional phenomena of inherently different nature and there is likely no possible way of capturing all their aspects at the same time. The way each aspect is measured is another limitation, which is subject to additional considerations, such as instrument bias, sample size and other data uncertainties. This holds true for both sprawl and air pollution data. In addition, while spatial boundaries for blocks, counties etc., are useful in improving our understanding of the urban form and in identifying vulnerable populations, they do not necessarily align with air pollution boundaries.

On the other hand, research continuously moves forward to capture more dimensions of urban sprawl and air quality in more areas, which gives us access to more and bigger data. While there is a need to move beyond single-case studies and explore less-studied urban scales, such as blocks and neighborhoods (Artmann *et al*., 2019), there is a trade-off between precision and resolution (EPA, 2016). A national-level analysis may be limited in providing an overview and identifying patterns for further consideration. A more thorough examination drawing on higher quality data, mapping visualizations and context-specific information can be the next step of such an analysis and may reveal aspects of this story that would be invisible otherwise.

Lastly, the analysis utilized in this paper attempts to incorporate some demographic indicators into the relationship of sprawl and air pollution, which has been deemed useful elsewhere (see Artmann *et al*. 2019). Therefore, the focus is on identifying an association and not describing a causal mechanism behind this relationship. Perhaps, there are several other ways of measuring this association, such us using longitudinal data, which may overcome possible omitted variable bias, or through utilizing a county-level analysis, which may allow to include more environmental justice dimensions that can be visible in such scales. Also, using U.S. Census demographic indicators related to race and minority groups is based on self-identification and reflects a social, rather than a genetic or biological definition of race. Such an approach may contribute to naturalizing racial categorizations, but on the other hand, it can enhance awareness of unequal environmental impacts and built environment choices. Nevertheless, the analysis can provide new insights in the ongoing discussion of more compact and sustainable urban development patterns and inform researchers of the particular dimensions of sprawl that may require further focus, such as street accessibility and urban, built-up density.

Conclusions

This paper employed a regression analysis approach to identify possible links between urban sprawl and environmental justice indicators in US territories. The sample was composed of 168,607 blocks with assigned characteristics that included ozone levels, air toxics cancer risk, sprawl/compactness dimensions and percentages of vulnerable population groups, such as children, seniors, and linguistically isolated racial minorities, with low income and low education levels. The research question was whether individuals with vulnerable demographic characteristics who reside in less compact blocks have higher risks of being exposed to lower environmental quality, specifically high ozone concentrations and high cancer risk from air toxics.

Sprawl is a well-known unsustainable urban development pattern, which has been rapidly systematized in various cities of the world after the industrial era, but there is still a lot of uncertainty in terms of what sprawl really means and what would be the best way to measure it. The updated sprawl/compactness index by Smart Growth America utilized in this study, treats sprawl as a measurable phenomenon with measurable consequences for people. Therefore, it allows for a thorough examination of the relationship between sprawl dimensions and environmental justice indicators.

Literature addressing directly the synergies of environmental injustice and sprawl is very limited, but as seen previously, there are several studies that connect either sprawl with air pollution or sprawl with social discrimination. This paper moved forward to investigate the integrated links of those dimensions and found statistically significant associations among aspects of sprawl and environmental injustice indicators. The relationship among sprawl and ozone showed that less compact urban development can be harmful for human health and welfare of vulnerable populations, especially in terms of density and street accessibility. The link between sprawl and ATCR showed that sprawl, and specifically lower density and centering, may contribute to lower cancer risk from air toxics in the same populations, but a higher mix factor links to less ATCR. Nevertheless, both findings highlight that planning and policy making processes should protect individuals, groups and communities from unjust regimes.

The results also suggest that further research is needed to study those phenomena in the micro-level, and that both scholars and practitioners should not just be concerned of reducing sprawl, but instead focus on reducing those particular aspects of sprawl that pose significant environmental challenges for socially vulnerable population groups. First, there is a need to evaluate the combined risk of multiple environmental aspects, such as pollution from ozone concentrations and other air toxics in the neighborhood level, which can provide a better picture of social context and urban form characteristics, such as density, centering and street accessibility. This could help assess the extent to which, certain compactness dimensions, such as street connectivity and mix of jobs need to be promoted, while balancing factors such as urban and population density and centering of people and businesses. Along those lines, future work should also identify socially vulnerable neighborhoods, but with low levels of pollution that have achieved local innovation and community building through promoting a more compact urban development form.

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References

Agyeman, J. (2007). 11 Environmental justice and sustainability. Handbook of sustainable development, 171.
Amiri, A., & Zhao, S. (2019). Environmental justice screening tools: Implications for nursing. Public Health Nursing.
Artmann, M., Inostroza, L., & Fan, P. (2019). Urban sprawl, compact urban development and green cities. How much do we know, how much do we agree?.
Batty, M., Besussi, E., & Chin, N. (2003). Traffic, urban growth and suburban sprawl.
Beck, R., Kolankiewicz, L., & Camarota, S. A. (2003). Outsmarting Smart Growth. Center for Immigration Studies, Washington DC.
Bereitschaft, B., & Debbage, K. (2013). Urban form, air pollution, and CO2 emissions in large US metropolitan areas. The Professional Geographer, 65(4), 612-635.
Berrigan, D., Tatalovich, AZ., Pickle, L. W., Ewing, R. and Ballard-Barbash, R. (2014). Urban Sprawl, Obesity, and Cancer Mortality in the United States: Cross-sectional Analysis

and Methodological Challenges. International Journal of Health Geographics 13: 3.
Bruegmann, R. (2006). Sprawl: A compact history. University of Chicago press.
Burchell, R. W., Shad, N. A., Listokin, D., Phillips, H., Downs, A., Seskin, S., & Gall, M. (1998). The Costs of Sprawl-Revisited (No. Project H-10 FY'95).
Camagni, R., Gibelli, M. C., & Rigamonti, P. (2002). Urban Mobility and Urban Form: the Social and Environmental Costs of Different Patterns of Urban Expansion. Ecological economics, 40(2), 199-216.
Christiansen, P., & Loftsgarden, T. (2011). Drivers behind urban sprawl in Europe. TØI Report, 1136, 2011.
Cifuentes, P., Reichard, J., Im, W., Smith, S., Colen, C., Giurgescu, C., ... & Hood, D. B. (2019). Application of the Public Health Exposome Framework to Estimate Phenotypes of Resilience in a Model Ohio African-American Women's Cohort. Journal of Urban Health, 1-15.
Cohen, R. A., & Martinez, M. E. (2011). Health Insurance Coverage: Early Release of Estimates From the National Health Interview Survey, January–March 2011. National Center for Health Statistics.
Driver, A., Mehdizadeh, C., Bara-Garcia, S., Bodenreider, C., Lewis, J., & Wilson, S. (2019). Utilization of the Maryland Environmental Justice Screening Tool: A Bladensburg, Maryland Case Study. International journal of environmental research and public health, 16(3), 348.
Eid, J., Overman, H. G., Puga, D. and Turner, M. A. (2007). Questioning the Relationship between Urban Sprawl and Obesity. Journal of urban Economics 63: 385-404.
El Nasser, H. and Overberg, P. (2001, February 22). Wide Open Spaces: The USA TODAY Sprawl Index. Retrieved from https://usatoday30.usatoday.com/news/sprawl/main.htm.
Ewing, R. and Hamidi, S. (2014). Measuring Urban Sprawl and Validating Sprawl Measures. Report from National Cancer Institute, National Institutes of Health, Ford Foundation and Smart Growth America.
Ewing, R. H., Pendall, R., & Chen, D. D. (2002). Measuring sprawl and its impact (Vol. 1, p. 55). Washington, DC: Smart Growth America.
Freilich, R. H., Sitkowski, R. J., Mennillo, S. D. (2010). From Sprawl to Sustainability: Smart Growth, New Urbanism, Green Development, and Renewable Energy. American Bar Association, Chicago, Illinois.
Galster, G., Hanson, R., Ratcliffe, M. R., Wolman, H., Coleman, S., & Freihage, J. (2001). Wrestling sprawl to the ground: defining and measuring an elusive concept. Housing policy debate, 12(4), 681-717.
Gavrilidis, A. A., Niță, M. R., Onose, D. A., Badiu, D. L., & Năstase, I. I. (2019). Methodological framework for urban sprawl control through sustainable planning of urban green infrastructure. Ecological Indicators, 96, 67-78.
Gordon, P. and H. W. Richardson (1997). Are Compact Cities a Desirable Planning Goal? Journal of the American Planning Association 63(1): 95-106.
Grier, L., Mayor, D., & Zeuner, B. (2019). Assessing the State of Environmental Justice in Michigan.
Guo, C., Buchmann, C. M., & Schwarz, N. (2019). Linking urban sprawl and income segregation–Findings from a stylized agent-based model. Environment and Planning B: Urban Analytics and City Science, 46(3), 469-489.
Harris, J. (2018). The Relationship Between Renewable Energy Manufacturers and Host Communities.
Jaeger, J. A., Bertiller, R., Schwick, C., Cavens, D., & Kienast, F. (2010). Urban permeation of landscapes and sprawl per capita: New measures of urban sprawl. Ecological Indicators, 10(2), 427-441.
Johnson, M. P. (2001). Environmental Impacts of Urban Sprawl: a Survey of the Literature

and Proposed Research Agenda. Environment and planning A, 33(4), 717-735.
Kahn, M. (2001). Does Sprawl Reduce the Black/White Housing Consumption Gap? Journal of Housing Policy Debate 12, 1.
Kang, J. E., Yoon, D. K., & Bae, H. J. (2019). Evaluating the effect of compact urban form on air quality in Korea. Environment and Planning B: Urban Analytics and City Science, 46(1), 179-200.
Li, F., & Zhou, T. (2019). Effects of urban form on air quality in China: An analysis based on the spatial autoregressive model. Cities, 89, 130-140.
Morello-Frosch, R., & Jesdale, B. M. (2005). Separate and unequal: residential segregation and estimated cancer risks associated with ambient air toxics in US metropolitan areas. Environmental health perspectives, 114(3), 386-393.
Nguyen, D. (2010). Evidence of the impacts of urban sprawl on social capital. Environment and Planning B: Planning and Design, 37(4), 610-627.
Pastor Jr, M., Morello-Frosch, R., & Sadd, J. L. (2005). The air is always cleaner on the other side: Race, space, and ambient air toxics exposures in California. Journal of urban affairs, 27(2), 127-148.
Pratt, G., Vadali, M., Kvale, D., & Ellickson, K. (2015). Traffic, air pollution, minority and socio-economic status: addressing inequities in exposure and risk. International journal of environmental research and public health, 12(5), 5355-5372.
Rowangould, D., Rowangould, G., Craft, E., & Niemeier, D. (2019). Validating and Refining EPA's Traffic Exposure Screening Measure. International journal of environmental research and public health, 16(1), 3.
Sadd, J. L., Pastor, M., Morello-Frosch, R., Scoggins, J., & Jesdale, B. (2011). Playing it safe: Assessing cumulative impact and social vulnerability through an environmental justice screening method in the south coast air basin, California. International Journal of Environmental Research and Public Health, 8(5), 1441-1459.
Schlosberg, D. (2009). Defining Environmental Justice: Theories, Movements, and Nature. Oxford University Press.
Schweitzer, L., & Zhou, J. (2010). Neighborhood air quality, respiratory health, and vulnerable populations in compact and sprawled regions. Journal of the American Planning Association, 76(3), 363-371.
Sierra Club (1998). The Dark Side of the American Dream: The Costs and Consequences of Suburban Sprawl. Challenge to Sprawl Campaign, College Park, MD.
Stone Jr, B. (2008). Urban sprawl and air quality in large US cities. Journal of environmental management, 86(4), 688-698.
Stone Jr, B., & Rodgers, M. O. (2001). Urban form and thermal efficiency: how the design of cities influences the urban heat island effect. American Planning Association. Journal of the American Planning Association, 67(2), 186.
Tessum, C. W., Apte, J. S., Goodkind, A. L., Muller, N. Z., Mullins, K. A., Paolella, D. A., ... & Hill, J. D. (2019). Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure. Proceedings of the National Academy of Sciences, 116(13), 6001-6006.
Torrens, P. M., and Alberti, M. (2000). Measuring Sprawl. Association of Collegiate Schools in Planning Conference, Atlanta, GA.
U.S. Environmental Protection Agency (EPA), (n.d.). EJSCREEN: Environmental Justice and Screening Tool. Retrieved from https://www.epa.gov/ejscreen/overview-environmental-indicators-ejscreen.
U.S. Environmental Protection Agency (EPA), (2016). EJSCREEN: Environmental Justice and Screening Tool. EJSCREEN Technical Documentation.
U.S. Environmental Protection Agency (EPA), (2015a). Air Quality Guide for Ozone.
U.S. Environmental Protection Agency (EPA), (2015b). EPA's 2011 National-scale Air Toxics Assessment (NATA). Technical Support Document.

U.S. Environmental Protection Agency (EPA) Report, (2003). Addressing Community Concerns: how Environmental Justice relates to Land Use Planning and Zoning.

Walker, G. (2009). Beyond distribution and proximity: exploring the multiple spatialities of environmental justice. Antipode, 41(4), 614-636.

Wei, Y. D., & Ewing, R. (2018). Urban expansion, sprawl and inequality.

Wilson, B., & Chakraborty, A. (2013). The Environmental Impacts of Urban Sprawl: Integrating New Evidence and Emergent Issues. Sustainability, 5 (8) (2013), pp. 3302–3327

Woo, B., Kravitz-Wirtz, N., Sass, V., Crowder, K., Teixeira, S., & Takeuchi, D. T. (2019). Residential Segregation and Racial/Ethnic Disparities in Ambient Air Pollution. Race and Social Problems, 11(1), 60-67.

Zhao, P. (2013). The impact of Urban Sprawl on Social Segregation in Beijing and a Limited Role for Spatial Planning. Tijdschrift voor economische en sociale geografie, 104(5), 571-587.

Zhao, J., Gladson, L., & Cromar, K. (2018). A Novel Environmental Justice Indicator for Managing Local Air Pollution. International journal of environmental research and public health, 15(6), 1260.

Zhao, Z. and Kaestner, R. (2010). Effects of Urban Sprawl on Obesity. Journal of Health Economics 29: 779-787.