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Sulfur dioxide exposure and environmental justice: a multi–scale and source–specific perspective

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ABSTRACT

Recent studies examining racial and ethnic inequities in exposure to urban air pollution have led to advances in understanding the nature and extent of overall concentration exposures by pollutant, demarcated by disadvantaged groups. However, the stability of inequities at various spatial units and the exposure by air pollution sources are often neglected. In this case study from the Dallas–Fort Worth (Texas, USA) area, we used Geographic Information Systems (GIS) and an air dispersion model to estimate environmental justice impacts at different spatial scales (i.e., zip code, census tract, block group) and by source (i.e., industrial pollution sources, vehicle pollution sources, industry and vehicle pollution sources combined). Using whites as a reference, blacks and other races were more likely to be exposed to higher sulfur dioxide (SO_2) concentrations although the Odds Ratio (OR) varied substantially by pollution source type [e.g., industrial pollution source based: (OR=1.80; 95% CI (Confidence Interval): 1.79–1.80) vs. vehicle pollution source based: (OR=2.70; 95% CI: 2.68–2.71)] and varied less between spatial scales [for vehicle pollution sources, (OR=2.70; 95% CI: 2.68–2.71) at the census tract level but was (OR=2.54; 95% CI: 2.53–2.55) at the block group scale]. Similar to the pattern of racial inequities, people with less education (i.e., less than 12 years of education) and low income (i.e., per capital income below $20 000) were more likely to be exposed to higher SO_2 concentrations, and those ORs also varied greatly with the pollution sources and slightly with spatial scales. It is concluded that the type of pollution source plays an important role in SO_2 pollution exposure inequity assessment, while spatial scale variations have limited influence. Future studies should incorporate source–specific exposure assessments when conducting studies on environmental justice.

Keywords: *Air pollution exposure, inequity, AERMOD, spatial scale, GIS*

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1. Introduction

Air pollution is recognized as a priority global health issue, affecting millions in both the developed and developing world (Brauer et al., 2012). Early studies have found that socioeconomic disparities in air pollution exposure and related health effects are prevalent (Zanobetti and Schwartz, 2000; O'Neill et al., 2003). Identification of susceptible and disadvantaged socioeconomic status (SES) groups at the greatest risk of air pollution exposure is critical for accurately estimating the adverse outcomes of air pollution and may provide additional explanations for inconsistency in results between studies.

For the purpose of fair treatment and meaningful involvement of all people regardless of age, race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies, the field of environmental justice has been increasingly regarded as a critical component in environmental policy debates (O'Neill et al., 2003; U.S. EPA, 2009).

In the field of air pollution exposure justice, since Asch and Seneca (1978) first found that exposure to air pollution in the United States (based on micro data) was related to socioeconomic characteristics, increasing interest has been paid to the assessment of air pollution exposure inequities. The past 34 years have seen the study areas of environmental justice expand from the United States to other developed countries (e.g., Canada, New Zealand, Britain, France) and as well as developing countries (e.g., China, India). Methods used to measure the level of exposure to air pollution mainly include proximity models (Stretesky and Lynch, 1999), air dispersion models (Fisher et al., 2006); Geographic Information Systems (GIS) spatial interpolation models (Su et al., 2011), and land use regression models (Crouse et al., 2009). The final results of environmental justice assessment are generally presented using statistical indicators, such as OR (odds ratio), ER (excess ratio), RD (risk difference), and RR (relative risk) with the baseline reference group being whites in racial comparisons.

To date, studies on air pollution exposure justice have consistently shown that certain subgroups of the general population are likely to suffer higher levels of air pollution exposure, depending on socio–demographic characteristics such as race/ethnicity, educational attainment, age, and SES (Foos et al., 2008). For example, Marshall (2008) found that mean exposure to benzene, butadiene, chromium particles, and diesel particles was higher than average for people who are nonwhite in California's South Coast Air Basin. Kingham et al. (2007) found that the vehicle pollution (i.e., PM_{10}) inversely related to the percentage of Europeans in a census area unit in Christchurch, New Zealand. Llop et al. (2011) found that younger women, immigrants from Latin American counties, and those belonging to the lower social strata were exposed to higher NO_2 levels in Spain. Ma (2010) highlighted the fact that an increase in income level was positively associated with the higher levels of industrial pollution exposure in Henan province, China.

In summary, there have been a large number of quantitative studies examining social inequities based upon a calculated or measured geographic distribution of air pollution, usually across an urban area. Although researchers have made strides towards understanding the nature and extent of air pollution exposure inequities, at least three aspects have often been overlooked. First, most studies have shown air pollution exposure inequities at the census tract scale due to the lack of individual level data (Kingham et al., 2007). These studies generally neglected to account for potential variations in air pollution and SES across different classes of spatial units (e.g., U.S. “zip code” vs. “census tract” vs. “block group”). Results of air pollution exposure equity assessment may be sensitive to analysis at these various levels. Second, most previous studies only considered a single type of pollution source (e.g., industrial pollution sources or vehicle pollution sources) or an aggregated exposure measurement (e.g., PM_{10} from all sources) instead of multiple types of pollution sources which represent a closer approximation to actual air pollution exposure. Understanding the source components of exposure would allow for a more accurate assessment of health effects from dose–response relationships and would also allow for more targeted policy measures limiting exposure. Last, when researchers focused on differences or similarities of air pollution exposure inequity in different areas (e.g., between developed countries and developing countries), they usually ignored the exposure level difference that might exist inside the study area due to the variation of dividing lines (Zou et al., 2013).

As a toxic gas and a precursor to particulates in the atmosphere, sulfur oxide (SO_2) is mainly released during various industrial processes (e.g., smelters, coal–fired power plants) and contributed by trucks and cars with low–grade diesel fuel (Zhang and Iwasaka, 2001). Since SO_2 emissions have consistently decreased in most countries over the past decades (Smith et al., 2001), it is generally recognized as a low–risk pollutant by environmental scientists and epidemiologists. However, recent studies found that low concentrations of SO_2 are still possibly associated with adverse health effects (Bell et al., 2007). Furthermore, GIS have empowered researchers with a tool for conducting spatial analysis by coupling air pollution and socioeconomic data at a variety of spatial scales (Viel et al., 2011). Methods of air dispersion modeling also provide a novel way to estimate source–specific air pollution concentrations (Zou et al., 2010) which could help detect and understand source–specific exposure inequities.

Therefore, this study aims to use GIS and air dispersion modeling methods to examine whether disadvantaged groups (e.g., blacks, individuals with low income or less education) are more likely to be exposed to higher levels of SO_2. This study differs from previous studies in that we: (1) ascertained the impact and sensitivity of the adjustment of spatial scale on the results of SO_2 pollution exposure inequity; and (2) differentiated the results of exposure inequity by the type of SO_2 pollution source. Our results show utility on several fronts. First, results of this study can aid in determining an appropriate spatial scale and geographical extent for accurately ascertaining exposure inequity while estimating the size of the effects of arbitrary selection of scale in a particular case study. Second, our results can help decision–makers to understand the SO_2 pollution sources that are most responsible for exposure inequity.

2. Materials and Methods

2.1. Study area

The Dallas–Fort Worth (DFW) metropolitan statistical area (MSA) in Texas, United States was selected as the study site (Figure 1). The DFW MSA includes six counties (Dallas, Tarrant, Johnson, Ellis, Denton, Collin), and covers an area of 13 728 km^2, contains 983 census tracts, and had a total population of 4 827 940 in 2000, making it the 4th largest MSA in the United States (U.S. Census Bureau, 2008). As shown in Figure 1, while vehicle–based SO_2 pollution sources (i.e., roads) are distributed relatively evenly over the entire DFW MSA (which is especially obvious in Dallas County), the industrial based SO_2 pollution sources exhibit a more clustered pattern across the entire DFW area. For this reason, we hypothesize that the intensity of SO_2 pollution exposure across the study area differs between vehicle pollution sources and industrial pollution sources. This variability makes DFW an ideal study area to ascertain the influence of source contribution on SO_2 pollution exposure inequities.

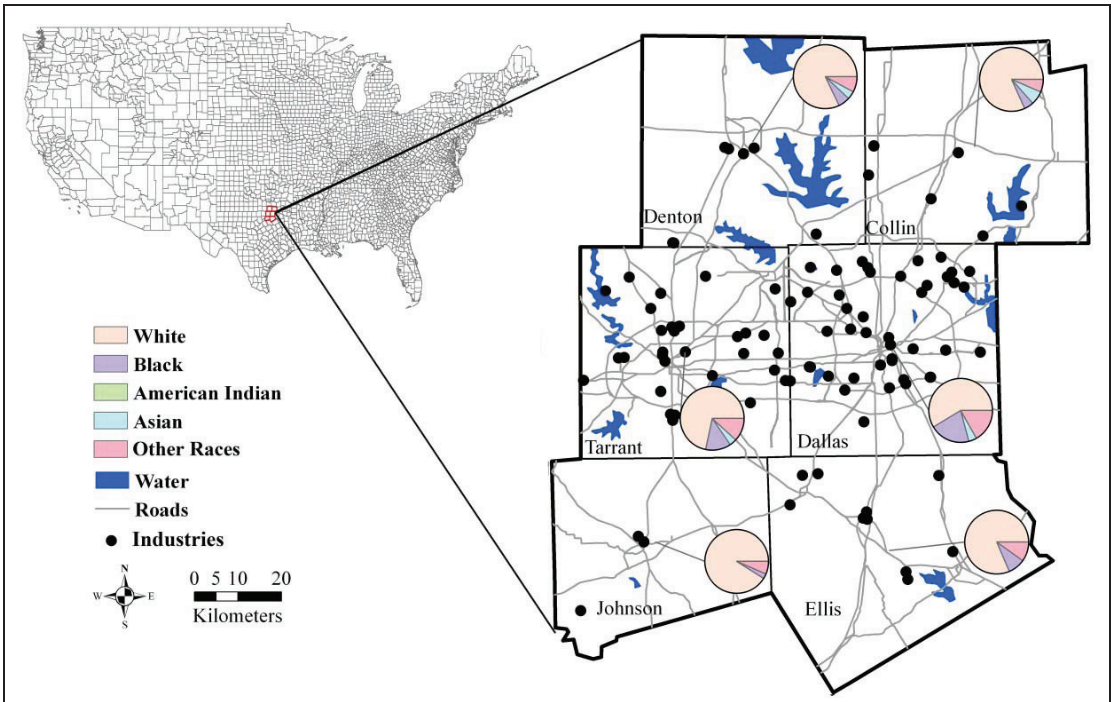

Figure 1. *Study area: DFW area in Texas, USA.*

2.2. Study design

In order to reach the study objectives outlined above, we broke down the entire study into three sub–processes: (1) scale–based (i.e., scales of zip code, census tract, block group) concentration computation; (2) socio–demographic (e.g., age, race, educational attainment, income) data categorization; and (3) logistic regression modeling which was used to calculate OR values that reveal inequities by socio–demographic characteristics. Details of these procedures are demonstrated below.

Scale–based concentration computation. As illustrated in the Introduction section, one of the objectives of this study is to examine whether spatial scale exerts influence on SO_2 pollution exposure inequity analysis. We therefore selected scales of zip code, census tract, and block group, with the intent that our results would provide solutions for inequity reductions. Census tracts are small, relatively permanent geographic subdivisions of a county or equivalent entity, block groups are geographic subdivisions of census tracts (U.S. Census Bureau, 2000a), and zip code boundaries are established for mailing distributions. In most cases, zip code areas are larger than census tracts and block groups (U.S. Census Bureau, 2000b).

In order to investigate the second study objective (i.e., differentiating the results of exposure inequity by the type of SO_2 pollution source), we employed source–specific annual SO_2 concentrations in the DFW area for the year 2000 using the AERMOD (American Meteorological Society / Environmental Protection Agency Regulatory Model) for which the details can be found in our previous work (Zou et al., 2010; Zou et al., 2011). Briefly, SO_2 pollution sources were categorized into industrial emissions and road emissions, both of which were retrieved from "1999 and 2002 National Emissions Inventory Data and Documentation" released by the U.S. EPA (2012). Industrial emissions were limited to industries (e.g., smelters, coal–fired power plants) with real SO_2 emissions, while road emissions were mainly contributed by trucks and cars with low–grade diesel fuel. Although the simulated traffic–based concentration would be much more accurate using traffic information about those trucks and cars, such data are often not available, especially for the time period (i.e., 2000) of this study. In addition, the reliability of these emission data for source–specific SO_2 pollution modeling in the same study area was validated in previous studies (Zou et al., 2009; Zou et al., 2010), confirming that local SO_2 emissions were the most likely contributor to the increased SO_2 concentration in the study area in 2000. Accordingly this study does not consider the influence of long–range transportation on SO_2.

After the preprocessing of data mentioned above, we calculated scale concentrations by two procedures. First, based on simulated SO_2 concentrations at locations of discrete receptors (i.e., including regular grid receptors at interval of 1 km and those manually created at locations of emission sources and traffic intersections), we tested the performance of ordinary Kriging (OK), inverse distance weighted (IDW), and Spline interpolation available in the Spatial Analyst module in ArcGIS 9.3, in order to create a spatially continuous surface of simulated annual SO_2 concentrations across the study area with a grid resolution of 500 m x 500 m of acceptable accuracy and eliminate the potential negative impacts that might be caused by "the black box interpolation method" employed by AERMOD plot module. In this process, an *F*–test was used to compare the simulated annual SO_2 concentrations from AERMOD with those predicted by each spatial interpolation method. Figure 2 shows the details of the interpolation process and its validation. In the end, the IDW spatial interpolation method was utilized due to its superior performance over other methods tested (Zou et al., 2013). Next, we computed the predicted annual SO_2 concentrations of each spatial unit at three different spatial scales by pollution source classification using a block Kriging method (Keshavarzi et al., 2011) (Figure 3). We used block Kriging because it can compute "geographic boundary" based concentration of a spatial unit from a continuous concentration surface, which greatly reduces the uncertainty caused by directly using point–interpolated data (Webster and Oliver, 2007).

Categorization of SO_2 concentration and socio–demographic data. Recent studies have suggested that low, chronic concentrations of SO_2 are not necessarily unrelated to adverse health effects. For example, associations between low birth weight and low exposure [i.e., below the National Air Quality Standard (NAQS) released by U.S. EPA] to SO_2 have been demonstrated (Bell et al., 2007). Therefore, instead of using standard health guidelines of air quality (e.g., the WHO guidelines) (WHO, 2005), this study reclassified source–specific SO_2 concentrations for each spatial unit as either relative low concentration or high concentration (of "air pollution") depending on whether its value was above or equal to/below the mean value (shown in Table 1) over the entire study area at each spatial scale. This classification scheme has actually been implemented by Kingham et al. (2007) in a environmental justice study to distinguish air pollution sources (i.e., domestic, vehicle, and industrial sources), in which air pollution exposure was explored by calculating the mean levels of predicted annual exposure among different age groups and ethnic groups.

Table 1. *Statistic characteristics of annual SO_2 concentration for a specific spatial unit by pollution source classification (unit: µg/m^3)*

Spatial Scale	Pollution Source	Median Concentration	Mean Concentration	Population (%) [a]
Zip code	Industrial pollution source	0.04	0.11	15.6%
	Vehicle pollution source	0.26	0.30	55.1%
	Combined [b]	0.36	0.41	50.7%
Census tract	Industrial pollution source	0.04	0.10	15.3%
	Vehicle pollution source	0.35	0.38	38.2%
	Combined	0.45	0.48	37.5%
Block group	Industrial pollution source	0.04	0.10	16.0%
	Vehicle pollution source	0.36	0.38	39.5%
	Combined	0.45	0.48	40.1%

[a] *Population (%) denotes the percent of population categorized as "with relative high SO_2 concentrations"*

[b] *Combined industrial and vehicle pollution sources*

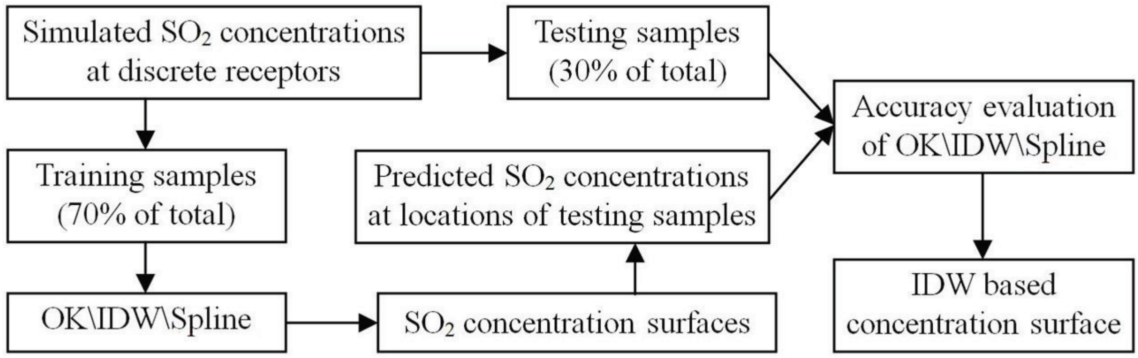

Figure 2. *Flowchart of spatial interpolation.*

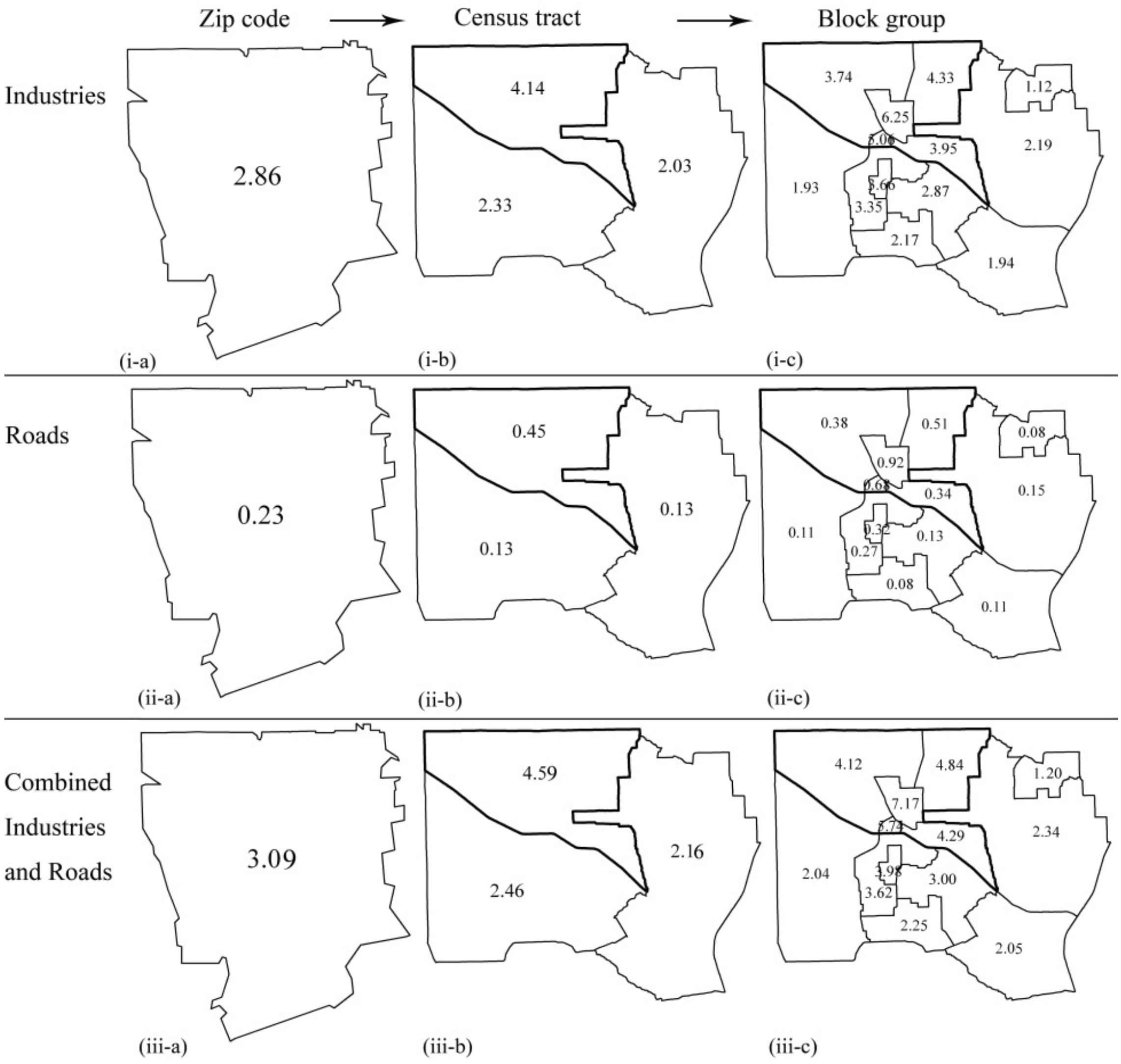

Figure 3. *Illustration of scale assimilation for SO_2 concentrations (unit: µg/m^3) in a specific spatial unit over scales (i, ii, iii denotes industrial, vehicle, combined industrial and vehicle pollution sources based SO_2 concentrations, respectively; a, b, c denotes county, census, and block group scale, respectively).*

Population data at the zip code, census tract and block group levels were retrieved from the Census 2000 Summary File 1 (U.S. Census Bureau, 2000c), while the geographic boundaries of spatial scale were obtained from the Census 2000 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line dataset (U.S. Census Bureau, 2000d). The average population at the zip code, census tract and block group levels are denoted by 21 686, 4 911 and 1 440 respectively. Proper categorization of socio–demographic characteristics is a key step in the assessment of exposure justice to air pollutants. In line with previous studies (Zanobetti and Schwartz, 2000; Gwynn and Thurston, 2001; Pope et al., 2002; Ou et al., 2008), we selected age, race, educational attainment, and income as the socio–demographic characteristics of focus in this study. These characteristics were categorized into different levels for each of the three spatial scales based on the reference category for comparison based on previous studies in the environmental justice literature. Age was classified into three levels of less than 14 years old, more than 60 years old, and 15 to 60 years old was selected as the reference category. Race was classified into five groups: blacks, American Indians, Asians, other races, and whites (reference category). Educational attainment was classified into four levels of less than 4 years, 5 to 8 years, 9 to 12 years, and more than 12 years (reference category). Per capital income was classified into two levels of below \$20 000, and above \$20 000 (reference category).

Logistic regression modeling. Once the sources of environmental pollution and the method for approximating exposure to the risk are determined in a quantitative environmental justice study, a statistical method can then be used to analyze the collected data and to draw conclusions about the inequities by social–demographic factors. We selected logistic regression modeling as our analyses technique due to the study objectives. Logistic regression is commonly utilized to model the probability of a binary outcome such as a logistic function of independent variables. Detailed principles of logistic regression modeling are as follows.

$$\text{odds} = \frac{P}{1-P} \tag{1}$$

$$\log(\text{odds}) = \text{logit}(P) = \ln\left(\frac{P}{1-P}\right) \tag{2}$$

$$\ln\left(\frac{P}{1-P}\right) = a + bX \tag{3}$$

$$\frac{P}{1-P} = e^{a+bX} \tag{4}$$

$$P = \frac{e^{a+bX}}{1+e^{a+bX}} \tag{5}$$

$$\text{OR} = \frac{P_1/(1-P_1)}{P_2/(1-P_2)} \tag{6}$$

where, "odds" is the probability of the outcome event to occur (i.e., "P") divided by the probability of the event not to occur (i.e., "$P/1–P$"). OR indicates the relative value by which the "odds" of the outcome increase (i.e., OR greater than 1.0) or decrease (i.e., OR less than 1.0) (Hilbe, 2009). "e" is the exponential constant, equal to 2.71828. "P_1" denotes the probability of the case group being exposed to air pollution. "P_2" denotes the probability of the control group being exposed to air pollution. "X" represents the explanatory variables which are either interval–level or "dummy", a, b represent partial regression coefficients of independent variable "X".

The logistic regression analyses in this study were carried out in SPSS version 17. In this process, the "spatial units" with relative high SO_2 concentrations were coded as "1", while the ones with low SO_2 concentrations were coded as "0". Consequently, these coded high/low SO_2 concentrations were used as the dependent variable. Similarly, the categorization results of social demographical factors were coded (e.g., the reference category was coded as 0) and used as independent variables. The indicator was set first as reference category. Meanwhile, the population amount of relative high/low SO_2 concentrations in each category by different social demographical characteristics were input correspondingly as weight cases.

3. Results and Discussion

3.1. Inequity in exposure to SO_2 concentrations by age

Table 2 shows the ORs of exposure to source–specific SO_2 by age at different spatial scales. We used the age range of 15–60 as the reference category as it has been used in previous studies (Bates et al., 1990; WHO, 2010). At most spatial scales, results show that persons over the age of 60 had greater risk of being exposed to SO_2 concentrations from vehicle pollution sources and combined industrial and vehicle pollution sources. For example, the OR of being exposed to SO_2 concentrations from vehicle pollution sources for people over the age of 60 is 1.15 (95% CI: 1.14–1.16) at the census block group scale. Persons over 60 had a lower exposure OR based on industrial pollution sources (OR: 0.97; 95% CI: 0.96–0.97) at the census tract scale.

From the spatial scale perspective, Table 2 shows that people under 14 and people over 60 had similar ORs of being exposed to SO_2 levels from industrial pollution sources and combined industrial–vehicle pollution sources at the block group and census tract scales. This may be explained by the fact that SO_2 pollution caused by industry activities in a block group or census tract are less variable while it might not be the case for larger zip code areas. However, when taking vehicle pollution sources into account, these two groups (i.e., those younger than 14 and those older than 60) had similar ORs at scales of zip code and block group.

3.2. Inequity in exposure to SO_2 concentrations by race

Table 3 shows the ORs of exposure to source–specific SO_2 concentrations by race at different spatial scales. From Table 3, it is clear that blacks and other races were more likely to be exposed to elevated SO_2 concentrations caused from all three categories of pollution sources. For example, the ORs of being exposed to SO_2 concentrations from industrial–, vehicle–, and combined industrial and vehicle based pollution sources for blacks at the census tract scale were 1.80 (95% CI: 1.79–1.80), 2.70 (95% CI: 2.68–2.71), and 2.56 (95% CI: 2.55–2.57), respectively.

Table 2. *Odds Ratios (ORs) and 95% Confidence Intervals (CI) of source–specific SO_2 exposure by age*

Spatial Scale	Age	Industrial Pollution Sources	Vehicle Pollution Sources	Combined Industrial and Vehicle Pollution Sources
Zip code	15–60	Ref [a]	Ref [a]	Ref [a]
	0–14	1.00 (1.00, 1.01) [b]	0.96 (0.95, 0.96)	0.99 (0.98, 0.99)
	>60	1.01 (1.00, 1.01) [b]	1.08 (1.07, 1.08)	1.09 (1.08, 1.10)
Census tract	15–60	Ref [a]	Ref [a]	Ref [a]
	0–14	1.03 (1.02, 1.03)	1.06 (1.05, 1.06)	1.01 (1.01, 1.02)
	>60	0.97 (0.96, 0.97)	0.85 (0.84, 0.85)	1.07 (1.06, 1.08)
Block group	15–60	Ref [a]	Ref [a]	Ref [a]
	0–14	1.01 (1.01, 1.02)	0.96 (0.95, 0.96)	1.01 (1.00, 1.01)
	>60	0.98 (0.98, 0.99)	1.15(1.14, 1.16)	1.07 (1.06, 1.08)

[a] *Reference category*
[b] *$p>0.05$, others: $p\leq 0.05$*

Table 3. *Odds Ratios (ORs) and 95% Confidence Intervals (CI) of source–specific SO_2 exposure by race*

Spatial Scale	Race	Industrial Pollution Sources	Vehicle Pollution Sources	Combined Industrial and Vehicle Pollution Sources
Zip code	White	Ref [a]	Ref [a]	Ref [a]
	Black	1.84 (1.83, 1.85)	2.58 (2.56, 2.59)	2.58 (2.56, 2.59)
	American Indian	1.05 (1.03, 1.06)	1.19 (1.17, 1.21)	1.11 (1.09, 1.12)
	Asian	1.19 (1.18, 1.20)	1.39 (1.37, 1.40)	1.22 (1.21, 1.23)
	Other race	1.51 (1.50, 1.51)	2.67 (2.65, 2.68)	2.50 (2.49, 2.52)
Census tract	White	Ref [a]	Ref [a]	Ref [a]
	Black	1.80 (1.79, 1.80)	2.70 (2.68, 2.71)	2.56 (2.55, 2.57)
	American Indian	1.05 (1.03, 1.06)	1.15 (1.13, 1.17)	1.13 (1.11, 1.15)
	Asian	1.10 (1.09, 1.11)	0.94 (0.93, 0.95)	1.01 (1.00, 1.02) [b]
	Other race	1.58 (1.57, 1.59)	2.14 (2.12, 2.15)	2.22 (2.21, 2.23)
Block group	White	Ref [a]	Ref [a]	Ref [a]
	Black	1.80 (1.79, 1.81)	2.54 (2.53, 2.55)	2.49 (2.48, 2.50)
	American Indian	1.04 (1.03, 1.06)	1.14 (1.12, 1.16)	1.11 (1.09, 1.13)
	Asian	1.12 (1.11, 1.13)	0.93 (0.92, 0.94)	1.02 (1.01, 1.02)
	Other race	1.58 (1.57, 1.59)	2.07 (2.06, 2.08)	2.10 (2.09, 2.12)

[a] *Reference category*
[b] *$p>0.05$, others: $p\leq0.05$*

Meanwhile, Table 3 also demonstrates that the inequities by race are largely consistent at different spatial scales, especially for those between scales of census tract and block group. For example, ORs of being exposed to SO_2 concentrations from industrial– based pollution sources for Blacks at the census tract and block group scales are almost the same, with the OR being 1.80 (95% CI: 1.79–1.80) and 1.80 (95% CI: 1.79,1.81), respectively. The only exception is that ORs (both less than 1.0) of being exposed to SO_2 concentrations from vehicle–based pollution sources for Asians at scales of census tract and block group vary more widely (1.39, 95% CI: 1.37–1.40) at the zip code scale.

3.3. Inequity in exposure to SO_2 concentrations by educational attainment

Table 4 shows the ORs of being exposed to source–specific SO_2 concentrations by educational attainment at the different spatial scales. Table 4 indicates that people with less educational attainment are exposed to higher levels of SO_2 concentrations caused by all categories of pollution sources. For example, while individuals with less than four years of education have the highest OR (1.66, 95% CI: 1.64–1.68) of being exposed to industrial pollution SO_2 concentrations at the block group scale, the corresponding ORs for people with 5–8 years of education and those with 9–12 years of education were 1.57 (95% CI: 1.55–1.58) and 1.26 (95% CI: 1.25–1.27), respectively.

Table 4 also shows that inequities in exposure to SO_2 concentration by educational attainment were fairly consistent across spatial scales and pollution source types. However, although the ORs by educational attainment level are consistent at the census tract and block group levels, those at the zip code scale still exhibited relatively greater differences.

3.4. Inequity in exposure to SO_2 concentrations by income

Table 5 shows the ORs of being exposed to source–specific SO_2 concentrations by income at the different spatial scales. Table 5 indicates that people with per capital income below $20 000 are exposed to higher levels of SO_2 concentrations caused by all categories of pollution sources. For example, this population group have the highest OR (2.73, 95% CI: 2.72–2.75) of being exposed to combined industrial vehicle pollution SO_2 concentrations at the zip code scale.

Table 5 also shows that inequities in exposure to SO_2 concentration by income were fairly consistent across spatial scales and pollution source types. However, although the ORs by income levels are consistent at the census tract and block group levels, those at the zip code scale still exhibited relatively greater differences.

3.5. Contributions

This study examined racial and socio–demographic inequities in exposure to source–specific SO_2 pollution at three spatial scales (zip code, census tract, block group) in the DFW metropolitan area. While the results echoed previous findings about the association between air pollution exposure and education (e.g., Jerrett et al., 2004; Miller et al., 2007), they also provided some new insights widely applicable to environmental exposure inequity research.

The study results disclose that while discrepancy of inequality in exposure to SO_2 concentration by educational attainment and race are largely not significant with the change of spatial scale and pollution source type, it is occasionally the case for inequality in exposure to SO_2 concentration by age. This might be attributed to the absolute values of ORs, as the air pollution exposure inequity results with ORs around 1.0 generally were relatively unstable and thus leading to unrecognized, slight scaling effects. From the discussion above, we conclude that the influence of spatial scale is not significant in analyzing SO_2 pollution exposure inequity when absolute ORs are much higher than 1.0.

Recently, the literature is stressing the necessity of differentiating air concentrations by pollution source type (Spira–Cohen, 2011), as it aids policy makers in taking accurate and effective action. However, in the case of air pollution exposure inequity, current studies primarily focus on exploring exposure inequity by regulating air pollution monitoring data without distinguishing pollution sources (Kingham et al., 2007). Although such studies are theoretically helpful for measuring each individual's air pollution exposure, they are limited by the inability to ascertain the potential pollution source type of exposure. Using air dispersion modeling results, this study for the first time explored inequities in source–specific SO_2 pollution exposure at different scales. The results revealed a discrepancy of inequity in exposure to SO_2 pollution from different pollution sources by age, race, educational attainment and income in the DFW area. These phenomena may be explained by the following facts. Elderly and retired persons are less likely to live in industrial areas than the reference group (i.e., those aged between 15 and 60) as they are not typically employed in those areas (Martins et al., 2004). Blacks are more likely to live in low–rent areas close to factories and roads with heavy traffic due to their disadvantaged economic situation. Inequity in exposure to SO_2 concentrations for American Indians and Asians were not as prominent as that for blacks, as the ORs were largely around or under 1.2. People with less than 12 years of education and low income are more apt to be living in proximity to industrial sites with relatively heavy traffic (Marshall, 2008; Ou et al., 2008). The results not only clearly provide information about pollution sources that caused the differences in exposure to SO_2 for specific socio–demographic groups, but also can help us to design reasonable interventions to reduce their vulnerability to air pollution due to the geographic variation of traffic and industry pollution.

3.6. Limitations

As a first step towards analyzing air pollution exposure inequity in terms of multi–scale and sources–specific perspective, limitations are inevitable.

First of all, it is necessary to compute exposure intensity at the individual level if we want to obtain highly accurate information about people's air pollution exposure inequity and by pollution source contribution in an area (Gilbert, 2009). However, it is too difficult to achieve this goal at this current stage due to cost, individual mobility, monitoring density, and the unavailability of air pollution concentration data provided by discrete monitoring sites. Although this study is among the first that use currently preferable air dispersion models (AERMOD) to estimate source–specific SO_2 concentration surfaces over the entire study area, we still have to rely on ecological estimates of SO_2 concentration by pollution sources due to the lack of individual scale demographic data. In light of this, the results generated from this study need to be further validated with those from individual–scale analyses.

Secondly, SO_2 is not a good marker for traffic and hence conclusions regarding traffic sources could be different. In future studies, other traffic–related air pollutants could be introduced to further explore the conclusion discrepancy. Meanwhile, our adoption of mean SO_2 concentration as the dividing line to ascertain areas of "relatively high" and "relatively low" was based on excluding outlier that could affect mean and make it unreliable in this study. Therefore, it should be mentioned that the distribution pattern of data set has to be confirmed before determining the dividing line between high exposure and low exposure.

Last, other factors such as neighborhood characteristics and statistical methods could also cause OR variations in this study. Although previous studies did not highlight these problems as substantial, they will indeed occur in some scenarios. For example, some recent studies indicate residents in some lower income neighborhoods in urban areas in North American and Europe face a "double burden" of exposure to air pollution for those (Jerrett et al., 2001; Naess et al., 2007; Premji et al., 2007). As a result, further studies on the importance of study site type and extent (i.e., urban vs. rural areas) in assessing air pollution exposure inequity are needed.

Table 4. *Odds Ratios (ORs) and 95% Confidence Intervals (CI) of source–specific SO_2 exposure by educational attainment*

Spatial Scale	Educational Attainment	Industrial Pollution Sources	Vehicle Pollution Sources	Combined Industrial and Vehicle Pollution Sources
Zip code	>12	Ref [a]	Ref [a]	Ref [a]
	0–4	1.52 (1.50, 1.54)	2.96 (2.92, 3.01)	2.93 (2.88, 2.97)
	5–8	1.48 (1.47, 1.50)	2.29 (2.26, 2.32)	2.39 (2.37, 2.42)
	9–12	1.22 (1.21, 1.22)	1.53 (1.52, 1.55)	1.57 (1.55, 1.58)
Census tract	>12	Ref [a]	Ref [a]	Ref [a]
	0–4	1.64 (1.62, 1.67)	2.60 (2.56, 2.63)	2.65 (2.61, 2.68)
	5–8	1.57 (1.56, 1.59)	2.17 (2.15, 2.19)	2.36 (2.33, 2.38)
	9–12	1.28 (1.27, 1.29)	1.63 (1.62, 1.64)	1.67 (1.66, 1.68)
Block group	>12	Ref [a]	Ref [a]	Ref [a]
	0–4	1.66 (1.64, 1.68)	2.371 (2.339, 2.403)	2.48 (2.44, 2.51)
	5–8	1.57 (1.55, 1.58)	2.075 (2.054, 2.096)	2.23 (2.21, 2.26)
	9–12	1.26 (1.25, 1.27)	1.564 (1.553, 1.576)	1.62 (1.60, 1.63)

[a] *Reference category*

Table 5. *Odds Ratios (ORs) and 95% Confidence Intervals (CI) of source–specific SO_2 exposure by income*

Spatial Scale	Income	Industrial Pollution Sources	Vehicle Pollution Sources	Combined Industrial and Vehicle Pollution Sources
Zip code	>20 000	Ref [a]	Ref [a]	Ref [a]
	≤20 000	1.11 (1.10, 1.11)	2.48 (2.47, 2.49)	2.73 (2.72, 2.75)
Census tract	>20 000	Ref [a]	Ref [a]	Ref [a]
	≤20 000	1.02 (1.01, 1.02)	2.61(2.60, 2.62)	2.53 (2.52, 2.54)
Block group	>20 000	Ref [a]	Ref [a]	Ref [a]
	≤20 000	0.94 (0.94, 0.95)	2.54 (2.53, 2.55)	2.53 (2.52, 2.53)

[a] *Reference category*

4. Conclusions

This work explored SO_2 pollution exposure inequities by age, race, educational attainment and income by different air pollution sources (i.e., industry–, vehicle–, and combined industrial and vehicle pollution sources) at spatial scales of zip code, census tract and block group across the DFW metropolitan area in Texas, USA. The results confirm that exposure to SO_2 is the highest among the most disadvantaged groups (e.g., less educational attainment, blacks, low income). Each type of pollution source was shown to contribute significantly to SO_2 pollution exposure inequities. Moreover, this study is among the first to systematically demonstrate that spatial scale variations only exert limited influence on the results of inequity in exposure to SO_2 pollution, and that the influence is minimal between the scales of census tract and block group.

In view of the limitations mentioned above, future work should focus on refining the ORs by adjusting for a variety of potential confounding factors in the process of estimating SO_2 pollution exposure inequity. For example, principal component analysis and factor analysis could be employed to generate several socio–demographic indices. In addition, the work presented in this study could be extended, were the data available, by combining other air pollutants exposure data with demographic data at the individual scale (Marshall, 2008). In this way, it is believed that a better understanding of air pollution exposure inequities could be attained, which would be helpful for shaping the inequity distribution of exposure to air pollution.

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