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# Public Transit and Ambient Nitrogen Dioxide (NO2) Levels in Four Atlanta Neighborhoods

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ABSTRACT

Public transit and Ambient Nitrogen Dioxide ($NO_2$) Levels in Four Atlanta Neighborhoods

By

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INTRODUCTION: The aim of this study is to explore elements of the built environment related to transportation, including state and interstate roads, railroads, daily traffic and bus stops and their relationship to ambient nitrogen dioxide ($NO_2$) levels. Taking place in predominantly African American communities of Atlanta across more affluent and poorer census tracts, this study also considered SES demographics. This study will pay particular attention to identify associations between $NO_2$ levels and proximity to bus stops.

METHODS: $NO_2$ data (ug/kg) was sampled in 2012 and distance to transportation was estimated. SES data was taken from the 2010 American Community Survey (ACS) at the block group level for the 17 block groups where $NO_2$ readings were taken. A multiple linear regression was modelled to test the relationship between $NO_2$ and distance from roads, bus stops, railroads, and attributes such as average daily traffic while controlling for SES variables.

RESULTS: In multivariable models, controlling for each variable through stepwise selection, variance was attributed more so to site distance to state road (m) ($\beta$=-0.1564; CI (-0.2114, -0.1014)), distance from bus stops ($\beta$=-1.3226; CI(-2.0459, -0.5993)), and average annual daily vehicle counts ($\beta$=0.00178; CI (0.000484, 0.00308)), than to demographic differences. Once controlling for traffic variables, no SES variables where selected into the model. Using the maximum r-squared approach to variable selection, the final model included 3 variables and an adjusted r-squared of 0.3835.

DISCUSSION: We were able to identify elements of the built environment that contribute to the increase of $NO_2$ in an urban area. Results show that factors such as proximity to roads and bus stops plays a statistically significant role in increased $NO_2$ readings. While exploratory in nature, and despite stated limitations, we were able to identify a statistically significant association between bus stops, state roads and daily traffic counts and increased $NO_2$ levels.

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Author's Statement Page

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## 1.0 CHAPTER I: INTRODUCTION

### 1.1 Background

The majority of the world's population lives in urban areas, with the trend of urbanization set to continue (UN, 2019). With growing urbanization comes increased importance of exposure to urban pollution sources. Recent concerns about residential proximity to major roadways has stemmed from links to impaired fetal development, cardiovascular health (Peng,2018; Beckerman, 2012), and environmental injustice (Clark, 2017; Johnson, 2016). In the US, more than a third of nitrogen oxides and a quarter of particulate matter (PM) are emitted from roadways. With a sizable share of the US population (45 million) living within 100 meters of a road (Liu,2013), and an estimated 11.4 million living with 150 meters of a major road (Boehmer,2013) the potential for exposure is large. $NO_2$ interacts with the oxygen and water vapor in the atmosphere creating nitric acid which, in addition to sulfur dioxide, are the main sources of acid rain (Likens, 1979).

The sources of and health outcomes related to air pollution – including hazardous gases, chemical vapors, PM and metals - are routinely the subject of public health inquiry (Bazyar,2019). Chronic exposure to air pollutants such as nitrogen dioxide ($NO_2$) and black carbon (BC) are associated with negative health outcomes such as cardiovascular and respiratory diseases (Beckerman, 2012; Li,2016). Overwhelmingly emitted by gasoline and diesel engines, $NO_2$ is commonly used as a proxy for traffic-related air pollution. Focus has routinely been placed on residential proximity to roads and SES factors with studies finding that communities with low SES are associated with higher ambient $NO_2$. Unfair zoning practices (Jerrett,2007) result in the release of disproportionate amounts of hazardous materials near vulnerable communities (Johnson,2016). This has been cited as environmental injustice resulting in higher $NO_2$ in these communities.

Nitrogen dioxide exposures are classified as acute or chronic depending on the duration of exposure and can result in different health effects. Acute exposures are defined as exposure to elevated concentrations for a shorter duration of hours to days. Severe exposures can result in immediate or near immediate death. Even if not fatal, many acute exposures can result in permanent injury (National Research Council (US) Subcommittee on Rocket-Emission Toxicants,1998).

Chronic exposures to $NO_2$ are typically of lower concentrations over long periods of time of months or years. These kinds of exposures are linked to adverse respiratory outcomes, and are correlated with asthma prevalence (Studnicka et al., 1997), wheezing (Kramer et al., 2000), more severe asthmatic reactions (Strand et al., 1998), and hay fever. Traffic, power plants and residential heating are major sources of ambient $NO_2$ levels in urban environments.

Traffic produces a varied mixture of pollution containing both solid and gaseous organic and inorganic species that contribute to health consequences. Pollution is emitted through a number of sources. Tailpipe emissions, road dust, brake pad wear each produce differing compositions of pollution (Krall, 2018). In urban areas, air quality is greatly affected by the trends and regulation of road transportation. Because transportation is a major source of $NO_2$ in the environment, the U.S. Environmental Protection Agency has set regulations on both diesel and gasoline vehicles in order to comply with the Clean Air Act (EPA, 1963). Due to modernization, economic growth and zoning practices in the US, metropolitan expansion has resulted in a greater reliance on motor vehicles to move from residential areas to work. This dependence on motor transport has facilitated the construction of more roads and highways, thereby increasing the prevalence of people living near major roads (Parvez,2019).

Several methods are used to assess ambient air pollution including land use regression models and direct air sampling. $NO_2$ has been used as an estimate of specific contributions of traffic to ambient air pollution. Studies have found pollution concentrations increases at points where traffic flow is slowed or halted such as at bus stops or congested roads (Xing, 2019).

In Atlanta, the provider of public transit options is the Metro Atlanta Rapid Transit Authority (MARTA), which offers both rail and bus services to different parts of the metro-Atlanta region. Rail services by MARTA are powered through an electrified track construction, and while not without its own pollution footprint, generates limited local emissions. A greater focus is drawn to MARTA’s extensive bus transit offerings, the majority of which use diesel or compressed natural gas fuel.

**1.2 Research Questions**

The aim of this study is to explore transportation infrastructure elements of the built environment including state and interstate roads, railroads, and bus stops and their relationship to ambient $NO_2$ levels with consideration given to SES factors such as poverty rate, education attainment, and unemployment. We sampled in predominantly African American communities across four census tracts with varying levels of poverty (<20%, 21-30%,31-40%, >40%). This choice was made in order to observe the relationship between transportation covariates and $NO_2$ while holding race constant.  These findings may be used to inform future transit and regional development policy planning as well as increased awareness of traffic-related pollution.

**2.0 Chapter II: Literature review**

Studies exploring the adverse health effects of $NO_2$ on health have found positive associations between $NO_2$ and mortality. Tied to mortality from non-accidental causes such as hypertension, CVD, stroke and chronic obstructive pulmonary disease, increases of 10 μg/m$^3$ resulted in increases in hazard ratios between 1.02 and 1.05 (Atkinson,2018). Other studies have linked chronic $NO_2$ concentrations with common but less severe outcomes. Between 18-42% of asthma cases between 2000 and 2010 were attributable to air pollution, representing 141,900 - 331,200 of asthma cases (Alotaibi,2019)

A synthesis of near road studies conducted by Karner, compiled 42 papers written between 1978 and 2008 to characterize the relationship between various pollutants and roadside distance. (Karner, 2010) Papers that included information or findings on near-road concentration gradients were selected as part of the analysis with the assumption that sufficient data quality controls were conducted. Consideration was also given to weather conditions across studies. These data points were then normalized using two different methods. The first, normalized to the background, results in the relative concentration of pollutants between near road concentrations and those unaffected by the road. The second, normalizing to edge-of-road, compares the maximum expected concentration to other concentrations in the measured area. Using an edge of road normalization, pollutants decay to background between 115-570m from the road, while using a more traditional background normalization saw decay between 160-570m. Differences were attributed to inherent biases associated with background estimation. Using either normalization method, nitrogen dioxide saw high levels at the roadway and a gradual decline in concentration further from the roadside (Karner,2010).

To determine the efficacy of using $NO_2$ as a proxy for air pollution, researchers measured correlations between $NO_2$ and black carbon, particulate matter, sulfur dioxide, and carbon dioxide. Results suggest that air pollution measures taken in the winter were more correlated than in the summer, specifically, nitrogen dioxide with ultrafine particles (UFPs) and hydrocarbon organic aerosols (HOA). Furthermore, pollutants such as HOA, UFPs, and nitrogen oxides share common sources, namely traffic exhaust while sulfur dioxide and benzene were more commonly were emitted by industry (Levy,2014). Given that nitrogen dioxide is largely produced by the combustion of fossil fuels it is routinely used as a proxy for traffic related air pollution (Yanosky, 2008).

Studies aiming to assess the impact of different modes of road transport such as buses have been conducted in cities such as Hong Kong and Poland (Bogacki,2019; Xing,2017). One such study in Hong Kong was able to locate a bus route along a single road with relatively low traffic lights and other traffic obstructions (Xing,2019). This allowed researchers to isolate the effect of bus stops by taking measures of $NO_2$ and particulate matter ($PM_{2.5}$) every 5 stops. $NO_2$ and particulate matter concentrations were plotted for the bus route and it was found that the greatest spikes in air pollution measures were present shortly after a bus stop (Xing,2019).

Environmental injustice is defined by a disproportionate distribution of environmental health risks on more vulnerable communities, especially low-income and communities of color. (Clark,2017) Well documented in the US, a wide range of pollutants have been found at higher ambient concentrations in lower socioeconomic status areas. North American zoning is decentralized with specific homogenous zones for industry and retail necessitating longer travel between home, industry, and retail (Jerrett,2007). Disparities in air pollution exposure is often a result of these inequalities in zoning or regional planning based on a community's SES (Clark, 2017; Marshall 2014). A longitudinal study by Clark et al used LUR models to estimate the disparity in ambient air pollution associated with SES factors (Clark, 2017). The researchers found race to be the most pronounced differentiating demographic variable. Reduction of absolute ambient $NO_2$ concentrations was attributed to the reduction of the relative difference between white and nonwhite populations by 2.1 ppm between 2000 and 2010. Despite this, the relative difference persisted shrinking from 37% to 31% in 2010 (Clark,2017). Alternatively, using SES data and a GIS model approach, researchers in the Worcester, Massachusetts MSA found significant inverse associations between income, education; and positive associations between crowding and $NO_2$ at the block group level (Yanosky,2008).

The Massachusetts based study by Yanosky et al, developed a predictive model assessing the relationship between SES factors including low educational attainment, poverty rate, income, and crowding. Their GIS model, built using $NO_2$ measurements, was used to estimate $NO_2$ levels in both urban and rural environments. Using data from 418 block groups in the Worcester, MA area, they found positive correlations with poverty, lower educational attainment, and crowding while a negative correlation was established with income. Even after controlling for spatial autocorrelation, the natural clustering of like values in GIS analysis, associations stayed statistically significant. Each additional standard deviation increases of $NO_2$ was associated decreases of $9090 median household income, with corresponding rates of poverty, crowding, and low educational attainment increasing by 3.1%, 1%, 3.4%, respectively. This provides evidence that those with a lower SES are disproportionately affected by $NO_2$ exposure when compared to those of higher SES. (Yanosky,2008)

An ecological study conducted in France sought to observe the association between socioeconomic status and air quality and how the relationship has trended over time (Padilla, 2014). To do so, a composite “deprivation index” was constructed using family and household income, immigration status and mobility, employment and income, education, and housing taken at the sub-municipal French census block in four French cities- Lille, Paris, Marseille, and Lyon. $NO_2$ data was retrieved from local air monitoring networks for each city. This deprivation index was used to assess the relationship between SES and air quality taken at two points in time. It was found that while overall $NO_2$ concentrations trended downwards, the strength and direction of the association between low SES and $NO_2$ estimates varied between cities resulting in the inability to characterize an association (Padilla, 2014).

A similar conclusion was found when a study, conducted in New York, sought to observe the relationship between social stressors and air pollution to determine the combined chemical and non-chemical effect on childhood asthma (Shmool, 2014). Using data from the census and local government agencies, a GIS model was used to assess relationships between stressors and indicators as well as between stressors and ambient $NO_2$ levels. The study found that social stressors, such as high crime and crowding were not consistently correlated, nor were they correlated with SES factors such as poverty. Lastly, apart from crowding, social stressors were not correlated with ambient $NO_2$ levels (Shmool,2014).

## 3.0 Chapter III: Methods

### *3.1 Study Design*

Census tracts were chosen in majority (>80%) African American population in Atlanta based on four brackets of poverty corresponding to <20% in poverty, 20-29% in poverty, 30-39% in poverty, and >40% of population in poverty. All sampling was accomplished in October 2013 using the OGAWA Badge sampler, a passive sampler that allowed for greater flexibility in site selection (*Ogawa* USA, Pompano Beach, Florida). Samplers were deployed for 1 week at each location. Exposed Ogawa pads were refrigerated after exposure and shipped to RTI International for analysis. For quality control purposes, 20% duplicates and 10% blanks were also collected. A total of 120 samplers were deployed, and 116 were successfully retrieved.

### *3.2 Covariates*

Geospatial Data collected from the Atlanta Regional Commission (ARC) was used to map bus stops, railroads, state highways, and interstate roads. Once all GIS data was mapped, distance of each collection site from: state roads, interstate roads, railroads, and bus stops was calculated using a distance to hub function then saved as a variable for each $NO_2$ site. Traffic data was obtained in the form of average annual daily traffic (AADT) counts from Georgia department of transportation (GDOT) regional counters corresponding to each $NO_2$ collection site. GIS data was mapped, sorted, and analysis using QGIS 3.4 (QGIS dev team, Open source).

Data on race, education, and poverty status was compiled from the 2010 American community survey (ACS) at the block group level for the 17 block groups where $NO_2$ samples were taken. Proportions were generated using block group population for each variable. A correlation matrix was generated to observe for collinearity between variables.

### 3.3 Statistical Analysis

Using a statistical software package (SAS 9.4) univariate models for each variable included in the model was generated. Using Pearson's correlation, which is best utilized to observe linear correlations between two variables, matrices were generated to assess whether any strong associations existed between covariates. $NO_2$ site distributions were evaluated across quantiles for each variable. Lastly, covariates were first evaluated separately before model generation was completed using stepwise selection.  This selection method sequentially adds covariates based on statistically significant P-values <.05. To compare, a second selection approach, RMAX was used. This approach sequentially adds variables that have the largest effect on the R-squared value.

Sensitivity analyses were conducted to determine if the number of bus stops in a block group are affected by poverty or unemployment. Using QGIS, the number of bus stops in each block group was saved as a variable and a correlation table was generated between the number of bus stops and unemployment rate and poverty. This is important as the initial correlation assessment focuses on the relationship between the distance of bus stops from the measurement sites and the poverty level in that area. By comparing the count of bus stops across the tracts a more direct conclusion is possible.

## 4.0 Chapter IV: Results

$NO_2$ was measured as $NO_2$ mass (ug/kg) in four census tracts corresponding to 17 unique block groups. The mean was found to be 3712 ug/kg (SD: 934 ug/kg). A correlation table (Table 1) was created to assess the relationship between all variables considered in the analysis with attention given to Pearson coefficients greater than 0.60. Notably, distance from state and interstate roads was found to be co-linear resulting in the necessity to remove one. State road distance was chosen to remain in the model as state roads tended to be closer to the sampling sites and as a result would be more directly the source of $NO_2$ emissions.

To observe the individual effect of each variable on $NO_2$ mass, a univariate model was generated between each variable and $NO_2$ and included in table 2. For Univariate models, statistically significant beta estimates were found for each covariable of interest with the exceptions of distance from railroads and unemployment. All covariates were then included in the stepwise selection from which a multivariable regression model was estimated. After selection, the model included distance of state roads (m), railroad, bus stops as well as traffic volume as predictors. No SES indicators were selected into the model once controlling for built environment factors. Adjusted R-squared values for the stepwise selected model (Adj R-Sq=0.3835) was compared to the full model that included all covariates (Adj R-Sq= 0.3787). Adjusted R-squared is a modified version of the R-squared value that takes into account the number of variables in the model which increases if variables added to the model improve the model more than what would be expected by chance.

The final model included distance to bus stop (m), distance to state roads (m), and average daily traffic as statistically significant predictors. This means that variance was attributed more so to site distance to state road (m) (β=-0.1564; CI (-0.2114, -0.1014)), distance from bus stops (β=-1.3226; CI(-2.0459, -0.5993)), and average annual daily counts (β=0.00178; CI (0.000484, 0.00308)), than demographic differences. Given the small count of block groups, only 17 unique proportions were available for inference limiting the variance and lowering the power to identify trends. Using the maximum R-squared selection approach, we found that the same model was generated, validating variable selection. The final model included 3 variables and an adjusted R-squared of 0.3835 (Table 3).

As a sensitivity analysis we explored the relationship between the SES variables and the number of bus stops in a block group. We ran Pearson correlations between the number of stops in each block group and the unemployment and poverty rate. In Table 4 we show that no statistically significant correlations between poverty status nor unemployment rate with number of bus stops in a block group were observed.

**Table 4.1: Pearson correlation Table**

| | NO Mass | Railroad Distance (m) | low Educational attainment | Poverty | Unemployment | Distance form State Road | Avg. Daily Traffic | bus stop dist.(m) |
|---|---|---|---|---|---|---|---|---|
| NO Mass | 1.000<br>- | -0.171<br>0.066 | 0.238<br>0.010 | 0.347<br>0.000 | 0.109<br>0.245 | -0.495<br><.0001 | 0.212<br>0.036 | -0.33238<br>0.0003 |
| Railroad Distance (m) | -0.171<br>0.066 | 1.000<br>- | -0.589<br><.0001 | -0.420<br><.0001 | -0.234<br>0.011 | 0.611<br><.0001 | 0.092<br>0.365 | 0.08983<br>0.3376 |
| low Educational attainment | 0.238<br>0.010 | -0.589<br><.0001 | 1.000<br>- | 0.646<br><.0001 | 0.166<br>0.075 | -0.457<br><.0001 | -0.035<br>0.730 | -0.04968<br>0.5964 |
| Poverty | 0.347<br>0.000 | -0.420<br><.0001 | **0.646**<br>**<.0001** | 1.000<br>- | 0.319<br>0.001 | -0.553<br><.0001 | -0.036<br>0.727 | -0.19359<br>0.0373 |
| Unemployment | 0.109<br>0.245 | -0.234<br>0.011 | 0.166<br>0.075 | 0.319<br>0.001 | 1.000<br>- | -0.406<br><.0001 | -0.231<br>0.021 | -0.05492<br>0.5582 |
| Distance from State Road (m) | -0.495<br><.0001 | **0.611**<br>**<.0001** | -0.457<br><.0001 | -0.553<br><.0001 | -0.406<br><.0001 | 1.000<br>- | 0.020<br>0.844 | 0.2328<br>0.0119 |
| Avg. Daily Traffic | 0.212<br>0.036 | 0.092<br>0.365 | -0.035<br>0.730 | -0.036<br>0.727 | -0.231<br>0.021 | 0.020<br>0.844 | 1.000<br>- | -0.01525<br>0.8809 |
| bus stop dist.(m) | 0.33238<br>0.0003 | 0.08983<br>0.3376 | -0.04968<br>0.5964 | -0.19359<br>0.0373 | -0.05492<br>0.5582 | 0.2328<br>0.0119 | -0.01525<br>0.8809 | 1<br>- |

| Key |
|---|
| Pearson Correlation Coefficients |
| Prob > \|r\| under H0: Rho=0 |
| **Coefficient > 0.6** |

**Table 4.2: Basic statistics and univariate models**

*Note: basic statistics as well as the p-value of univariate regression models. $\sigma^2$ = Variance, $\sigma$ = Coefficient of Variation*

| Variable | N | Mean | Std Dev | Std Error | $\sigma^2$ | $\sigma$ | t value | Pr > \|t\| |
|---|---|---|---|---|---|---|---|---|
| $NO_2$ mass | 116 | 3711.99 | 934.65 | 86.78 | 873578.98 | 25.18 | | |
| $NO_2$ (ppm) | 116 | 11 | 3 | 0.25 | 7 | 25 | | |
| Distance from state road | 116 | 3848.37 | 2567.98 | 238.43 | 6594510.5 | 66.73 | -6.08 | **<.0001** |
| Distance from railroad | 116 | 1125.04 | 892.54 | 82.87 | 796633.9 | 79.33 | -1.86 | 0.0660 |
| average daily total traffic | 99 | 141022.42 | 108483.93 | 10903.04 | 11768762429 | 76.93 | 2.13 | **0.0355** |
| bus stop distance | 116 | 188.47 | 197.64 | 18.35 | 39061.6 | 104.86 | -3.76 | **0.0003** |
| Poverty | 116 | 0.268 | 0.18 | 0.017 | 0.032 | 66.69 | 3.95 | **0.0001** |
| Unemployment | 116 | 0.224 | 0.11 | 0.011 | 0.013 | 50.76 | 1.17 | 0.2451 |
| Low educational Attainment | 116 | 0.364 | 0.069 | 0.006 | 0.005 | 18.91 | 2.62 | **0.0100** |

**Table 4.3: Adjusted model using stepwise selection**

| Adjusted model using stepwise selection | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | DF | N | N missing | Parameter estimate | Standard Error | t Value | Pr > \|t\| | 95% Confidence Limits | | Adj R-Sq |
| **Intercept** | 1 | 99 | 17 | 4316.006 | 165.1893 | 26.13 | **<.0001** | 3988.064 | 4643.948 | **0.3835** |
| **Distance from state road** | 1 | | | -0.15642 | 0.0277 | -5.65 | **<.0001** | -0.21142 | -0.10142 | |
| **Distance from bus stop (m)** | 1 | | | -1.32257 | 0.36433 | -3.63 | **0.0005** | -2.04585 | -0.59929 | |
| **Avg daily Traffic** | 1 | | | 0.00178 | 0.000654 | 2.73 | **0.0076** | 0.000484 | 0.00308 | |
| Model: $NO_2$ mass= intercept + variable | | | | | | | | | | |

**Table 4.4: Pearson Correlation for Bus stop (N) and SES**

| Pearson Correlation Coefficients, N = 13 | | |
|---|---|---|
| | unemployment | Poverty status |
| Bus stops (N) | -0.49007<br>Pr > \|t\|= 0.0891 | -0.37374<br>Pr > \|t\|= 0.2084 |

## 5.0 Chapter V: Discussion

We were able to identify that distance from bus stops and state roads and annual average daily traffic have statistically significant relationships with $NO_2$ mass. Sociodemographic variables, such as unemployment or poverty status, have a lesser impact after controlling for the transportation variables. This increase in $NO_2$ emission at bus stops, as well as points of congestion, has been observed in Chinese studies on traffic emissions (Xing,2019). The associations between bus routes and increased $NO_2$ are present, likely due to the nature of buses and bus stops. Not only do buses typically produce a large amount of emissions, it is not uncommon for a bus to idle waiting for passengers at stops on busy routes. This may lead to the beta estimate for the effect of bus stop distance to be notably higher than distance to state roads.

Site selection was done such that race would be a relative constant across the study area by sampling in largely African American communities. While many studies in the US have identified SES as an indicator for increased ambient $NO_2$ levels, this study aimed to observe differences in built environment that may account for these differences. Variables such as proximity to roads, road traffic volume and distance to bus stops were focused on and play a statistically significant role in increased $NO_2$ mass levels. Once built environment factors were included in the model, SES factors lost statistical significance and were removed from the final model by software. This removal may be due to a modifiable areal unit problem. Data from sources such as the Census bureau are aggregated into groups and averaged for privacy. This means that, despite using the smallest scale, enough variance is not present to determine trends.

Attention was also given to whether block groups with higher poverty or unemployment had more bus stops than those with less poverty. In the case of this study, we found that poverty did not have a statistically significant correlation with either unemployment or poverty. This could be due to the extensive and uniform bus service offered by MARTA in the Atlanta region.

**5.1 Limitations**

Study limitations include reliance on ACS block group data for all major demographics. While expansive in topics and scope, ACS surveys are a rolled average of 5 years conducted at the Census level. This results in a large margin of error at the block group level. Moreover, given the few block groups the data was collected over resulted in only 17 distinct values for each demographic, severely limiting the ability to include demographic variable in the model. Despite these limitations, demographic data was included on basis that this study is exploratory in nature and does not seek to establish causal links between variables and outcomes.

Another limitation stems from the reliance on bus stop data from 2017. Data was not present for 2012, the year the samples were taken. A dataset was found for the year 2014 however it was not possible to verify the validity of the dataset given its source. Largely similar to the 2014 data set, to ensure the reliability of the data the 2017 dataset available on the Fulton county GIS database was selected instead. This does necessitate the assumption that there was no dramatic change in bus stops between 2012 and 2017 in the study area. Lastly, since all data was collected at the same point in time, it is impossible to draw any causal relationships. In addition, given the study's cross-sectional design and reliance on regression to adjust for confounding, limitations result in an inability to account for unknown and unmeasured confounders.

Finally, while model selection using either stepwise or R-max selection did result in the same model, this could be due to the greater variance of traffic variables when compared to SES measures. While the estimates regarding the relationship between traffic variables and $NO_2$ hold valid, this prevents any conclusions regarding the relationship between SES factors and ambient $NO_2$. In future studies, sampling across a larger area that corresponds to a greater number of census tracts could be used to alleviate this limitation.

**5.2 Conclusion**

This study contributes to the body of air pollution literature with its focus on exposure sources and GIS approach to identifying variables in the Atlanta area. While exploratory in nature, we were able to establish statistically significant correlations between bus stops, distance to road and daily traffic with increased $NO_2$ levels. Further study may be warranted to establish whether factors such as shorter residential distance from roads are associated with lower SES. City transit systems can employ more efficient buses and bus routes that allow for less idling and stops. Since the collection of the data in 2012, the city of Atlanta has incorporated newer buses allowing for potential follow up studies.

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