Geospatial Analysis on Toronto AQHI levels

Amr Shalaby, Ryan Siu, Burora Matthew Ruku

Abstract

In this paper, we explored the relationship between traffic volumes and air quality in Toronto, focusing on the Air Quality Health Index (AQHI) levels. By employing Python and SQL for data processing and QGIS for spatial analysis, we analyzed datasets from Environment and Climate Change Canada and the City of Toronto's Transportation Services Division. Our approach utilized statistical techniques like Kernel Density Estimates and Inverse Distance Weighting to uncover a nuanced interaction between urban traffic and air pollution levels. These findings should be useful to planning and environmental sustainability stakeholders at all levels of government.

1 Introduction

Urban air quality, a critical determinant of public health and environmental sustainability, has garnered increasing attention in recent years, particularly in the context of rapidly urbanizing cities. Among various pollutants, vehicular emissions stand as a primary contributor to urban air pollution.(3) Our research paper delves into the dynamics between traffic volumes and air quality in Toronto, examining how variations in vehicular traffic affect the city's air quality, as quantified by the Air Quality Health Index (AQHI).

Prior studies have extensively documented the impact of air pollutants on human health, ranging from respiratory ailments to cardiovascular issues.(1) However, there remains a gap in localized research that correlates specific urban traffic patterns with air quality variations. This study seeks to bridge this gap, focusing on Toronto, where the combination of dense population, bustling traffic, and diverse socio-economic factors creates a unique urban ecosystem. Understanding this connection is crucial for formulating effective urban planning and public health policies.

The relevance of our investigation is underscored by the evolving nature of urban environments and the escalating challenges they pose to sustainability and public health. In the case of Toronto, a city characterized by significant vehicular traffic, assessing the correlation between traffic volumes and AQHI offers insights into targeted strategies for pollution mitigation. Our research addresses unresolved questions regarding the temporal and spatial aspects of this correlation, exploring whether certain times of the day or specific areas within the city are disproportionately affected.

In our study, we adopted a methodology, that leverages datasets from the City of Toronto's Transportation Services and Environment and Climate Change Canada. We used Python for initial data processing and visualization, allowing us to delineate and understand the distribution of air quality values. For a deeper geospatial analysis, we employed QGIS, to map and analyze the spatial relationship between traffic and air quality. We also integrated Kernel Density Estimates and Inverse Distance Weighting, to uncover the intricate patterns linking traffic volumes to AQHI levels. This multi-faceted approach allowed us to extend beyond the scope of traditional statistical methods, offering a more sophisticated and nuanced understanding of the factors influencing urban air quality.

Our research paper presents an in-depth analysis of the interplay between traffic volumes and air quality in Toronto. By investigating this relationship and identifying key patterns and trends, our study contributes to the broader discourse on urban environmental management and public health promotion. The findings are expected to offer valuable recommendations for urban planners, policymakers, and public health officials, guiding interventions that can effectively address the challenges posed by traffic-related air pollution in urban settings.

2 Literature Review

2.1 Impact of Traffic-Related Air Pollution on Health in Canada: Brauer, Reynolds, and Hystad

Background and Scope

In the realm of environmental health, the intersection of urban development and public health is gaining increasing prominence. A significant component of this nexus is traffic-related air pollution (TRAP) and its impact on population health. The study "Traffic-related air pollution and health in Canada" by Brauer, Reynolds, and Hystad provides a comprehensive analysis of this issue within the Canadian context.

Health Impacts of TRAP

The study underscores the severe health consequences of TRAP in Canada, drawing attention to a stark statistic: an estimated 21,000 premature deaths annually attributable to air pollution, eclipsing fatalities from motor vehicle accidents. The causal links established between TRAP and various health issues are alarming. Asthma exacerbation, the development of childhood and adult-onset asthma, deteriorating lung function, cardiovascular mortality, myocardial infarction, atherosclerosis progression, and lung cancer are among the critical health concerns linked to TRAP. The evidence is robust, with the study referencing numerous epidemiological and toxicological literature, including the classification of diesel engine exhaust as carcinogenic by the International Agency for Research on Cancer.

Exposure in the Canadian Context

The review of TRAP in Canada reveals that a significant portion of the population is at risk. Approximately 32% of Canadians, equating to around 10 million people, reside in high-exposure zones, typically within close proximity to major highways and urban roads. This high prevalence underscores the need for urgent public health interventions and policy responses.

Mitigation Strategies

The study discusses a spectrum of mitigation strategies, categorized as short-term and long-term approaches. Short-term strategies focus on immediate measures like vehicle emissions reduction and infrastructure modification. Long-term strategies emphasize holistic approaches such as integrated land-use planning and transportation management. The review highlights the effectiveness of combining these strategies for more cost-effective and impactful solutions. It also points to the potential benefits of promoting active transportation and integrated land-use planning, which would serve dual purposes: reducing air pollution and enhancing physical activity among the population.

2.2 Air Pollution and Health Risks Due to Vehicle Traffic: Kai Zhang and Stuart Batterman

Introduction

The research paper titled "Air pollution and health risks due to vehicle traffic" by Kai Zhang and Stuart Batterman presents a detailed study on the impacts of traffic congestion on air quality and public health. This review analyzes their methodology, findings, and implications in the context of environmental health sciences.

Methodology and Approach

Zhang and Batterman utilize simulation modeling to estimate the concentrations of nitrogen dioxide (NO2) and the associated health risks for both freeway and arterial road scenarios during peak traffic hours. The study leverages emission factors from two models (Comprehensive Modal Emissions Model and Motor Vehicle Emissions Factor Model version 6.2), traffic speed-volume relationships, dispersion models, and established concentration-response relationships. The research focuses on estimating health impacts related to emergency doctor visits, hospital admissions, and mortality due to NO2 exposure.

Key Findings

The author's study found non-linear effects of traffic volume on health risks. For freeways, it predicts a "U" shaped trend of incremental risks for on-road populations, while the risks for near-road populations remain flat at low traffic volumes. In contrast, for arterial roads, the incremental risks sharply increase for both on- and near-road populations as traffic volume rises. These variations are attributed to changes in emission factors, the NO2-NOx relationship, travel delays, and the duration of rush hours.

Implications for Public Health

Zhang and Batterman highlight the significant health risks posed by traffic congestion, especially in urban settings where large populations are exposed to vehicle emissions. The study suggests that health risks from congestion are potentially significant and that additional traffic can considerably increase these risks. The findings emphasize the need for effective traffic management and pollution control strategies to mitigate the adverse health impacts.

2.3 Effect of Road Traffic on Air Pollution - Evidence from COVID-19 Lockdown: Rossi, Ceccato, and Gastaldi

Introduction

"Effect of Road Traffic on Air Pollution: Experimental Evidence from COVID-19 Lockdown" by Rossi, Ceccato, and Gastaldi examines the impact of reduced traffic flows on air quality during the COVID-19 lockdown in Padova, Italy. This literature review encapsulates the key elements of their research, focusing on methodology, findings, and broader environmental implications.

Methodology and Context

The study leverages the unique opportunity provided by the COVID-19 lockdown - a period of drastic reduction in vehicular traffic - to analyze the relationship between traffic flows and air quality. The researchers employed statistical tests, correlation analyses, and multivariate linear regression models, focusing on non-rainy days in 2020 compared to 2018 and 2017. The study area, Padova, is characterized by high population density and significant pollution problems.

Key Findings

Rossi, Ceccato, and Gastaldi's analysis reveals a clear link between reduced vehicle flows and a decrease in concentrations of nitrogen oxides (NO, NO2, and NOx). However, no significant correlation was found between traffic reduction and particulate matter (PM10) levels. This finding is critical as it suggests that while traffic restrictions can effectively reduce nitrogen oxide pollution, they may not significantly impact particulate matter concentrations.

Public Health and Policy Implications

The study's findings have significant implications for urban planning and public health policies. The observed reduction in nitrogen oxides due to lower traffic volumes during the lockdown underscores the potential effectiveness of traffic restriction measures (like car-free days or odd-even number-plate schemes) in improving air quality. However, the lack of impact on PM10 levels suggests that additional measures might be required to address particulate matter pollution.

3 Data Sources

Our study utilizes two primary data sources: the Air Quality Health Index (AQHI) data from Environment and Climate Change Canada and the traffic volume data collected by the City of Toronto's Transportation Services Division.

Air Quality Health Index (AQHI)
The AQHI data, sourced from a network of air monitoring stations across Canada, is pivotal in assessing air quality. These stations collect real-time emissions data on key pollutants, such as ground-level ozone, particulate matter, and nitrogen dioxide. The network currently consists of 38 ambient air monitoring stations that collect data on key pollutants that represent the overall air quality.(4)

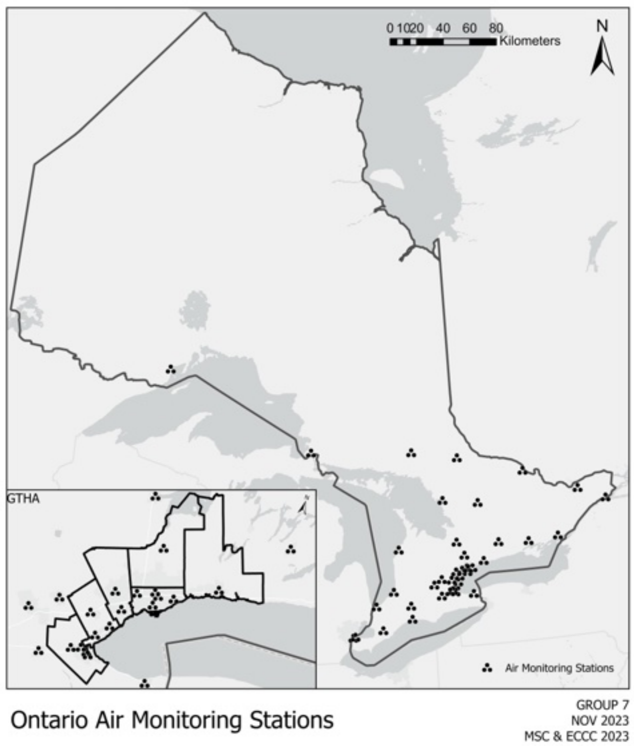

Figure 1: Ontario Air Monitoring Stations.

The AQHI is calculated from this data to quantify air quality on a scale from 1 to 10, with an additional category for very high pollution levels (10+). The following table outlines the AQHI levels and corresponding health messages for at-risk and general populations:

Health Risk	Air Quality Health Index	At Risk Population	General Population
Low	1 - 3	Enjoy your usual outdoor activities.	Ideal air quality for outdoor activities.
Moderate	4 - 6	Consider reducing or rescheduling strenuous activities outdoors if you are experiencing symptoms.	No need to modify your usual outdoor activities unless you experience symptoms such as coughing and throat irritation.
High	7 - 10	Reduce or reschedule strenuous activities outdoors. Children and the elderly should also take it easy.	Consider reducing or rescheduling strenuous activities outdoors if you experience symptoms such as coughing and throat irritation.
Very High	Above 10	Avoid strenuous activities outdoors. Children and the elderly should also avoid outdoor physical exertion.	Reduce or reschedule strenuous activities outdoors, especially if you experience symptoms such as coughing and throat irritation.

Table 2: Health Messages Associated with the Air Quality Health Index

Traffic Volume Data
The City of Toronto's traffic volume data is gathered from various sources for multiple purposes. It encompasses two main types: Automatic Traffic Recorder (ATR) Counts and Turning Movement Counts (TMCs). ATR Counts reflect segment-level volumes on specific streets, while TMCs provide detailed movements observed at specific intersections. This data includes total volumes segmented by direction, turning movement, and mode (car, truck, bus, pedestrian, cyclist, other). Each TMC comprises single-day data at one location, reported in 15-minute intervals. The data, available in various formats, references the City of Toronto's Street Centreline, Intersection File, and Street Traffic Signal datasets.(5)

Together, these two datasets offer a comprehensive foundation for analyzing the relationship between urban traffic volumes and air quality, enabling our investigation into the potential correlations and implications for urban planning and public health.

4 Method

4.1 ETL Pipeline Design

The extraction phase utilizes web scraping to extract the CSV files via parsing through http links on the Government of Canada Weather portal for the monthly air data. The monthly air data files amounted to 26 files that are ingested into the first staging layer, `stg_monthly_air_data` whose associated tables have the prefix `stg_` to indicated untreated, unfiltered, and only extracted staging data stored in stage schema as they are not in a production-ready state which is exclusive to public schema. Similarly, the geographical stations metadata including latitude, longitude, and other pertinent information are web scraped from a separate http portal and stored to `stg_geo_names` staging table.

Three additional columns are added to the staging tables; namely, `last_updated` timestamp, file source http link, and filename to trace any duplication, data corruption, or anomalous payload to isolate its source and also calculate the time between insertion into production schema and time of data acquisition from the government portal.Similarly, daily forecasts are also web scraped, capturing 533 files as a possible secondary resource and stored in `stg_monthly_forecasts`. However, the Traffic Volume Dataset's python REST API was not as mature as their R Connector so an R thread was instantiated under the python pipeline to capture the Traffic Volume via its R Library `opendatatoronto` to build `stg_traffic_volume` in the stage schema. The Extraction Layer, on average, spanned for 343.3 seconds or 85.8% of total pipeline execution time at 400.2 seconds.

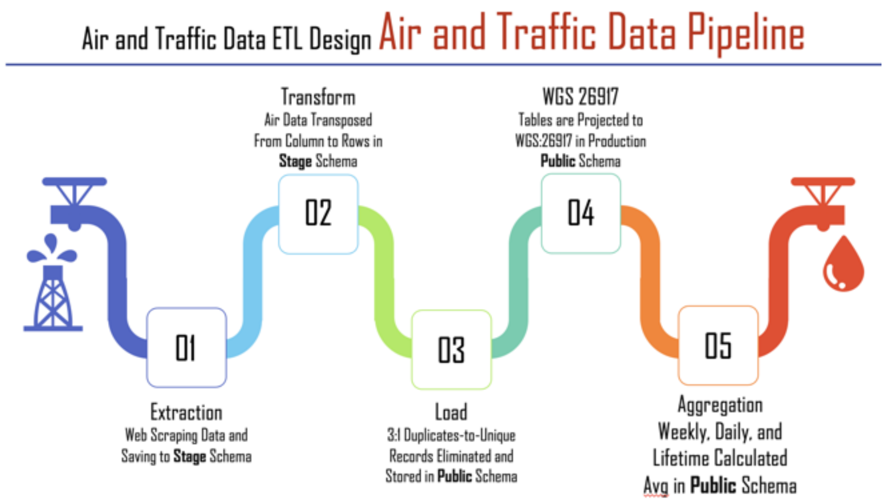

Figure 2: ETL Pipeline

4.2 Transformation Layer

The staging table `stg_monthly_air_data` in its untreated, scraped version was not usable as the geo-station identifiers were the columns and the air data measures were the rows. It has to be transposed into row-based geostation identifiers to join unto other tables using geostation identifier strings. Accordingly,`stg_monthly_air_data'` was transformed into `stg_monthly_air_data_transpose` in the stage schema.

4.3 Loading (Production) Layer

All the tables in the staging layer are ingested into "public" schema which is the production schema under four categories following the Data Warehouse Naming Standards:

1. Dimension Table whose prefix is `dim_` when signifying the contextual information of the weather stations.as to when they first became active, latitude, longitude, and other identifiers used pertinent to the geostation itself, not its measures. As such, `dim_geo_names` is the dimension table of the weather stations.

2. Facts Table whose prefix is `fact_` when capturing facts or measures from the weather stations. when capturing facts or measures from the weather stations. As such, `fact_monthly_air_data`, `fact_monthly_air_data_transpose`, `fact_monthly_forecasts`, and `fact_traffic_volume` were created in the "public" schema as they are now in an analytics-ready state.

3. Facts table whose suffix is `_proj` are the Postgis Tables created by Geopands with the binary `geometry` columns using WGS 26917 Projection such as `fact_air_data_proj` and `fact_gta_traffic_proj`.

4. Tables neither fall in fact nor dimensions are labeled with a suffix `_tbl`.such as `data_model_performance_tbl` that tracks each step and its execution time for code optimization.

The data duplication rate in the staging files was 3:1 (3 duplicate rows to 1 unique row) as multiple measures were taken in the same UTC Hour which required filtering by taking the most recent measure within the UTC Hour per weather station. The "Partition By" operation ensured the latter result was achieved.
The monthly air data, traffic data, monthly forecasts, and other projected Postgis Tables with geometry columns are ingested into a total of 12 analytics-ready tables with the added column `_last_inserted` timestamp to track timestamps from web scraping to insertion into the staging layer to the final readiness in production to account for the data lifecycle, flag outdated measures, optimize subprocesses, and validated every record's integrity from http source to analysis consumption. The production accounted for only 14.2% of total execution time and was capable of eliminating 75% of the duplicate rows autonomously without any hard code or user input.

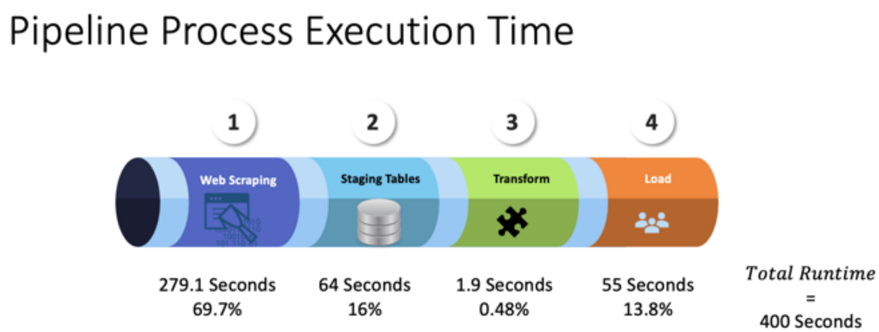

Figure 3: Pipeline Process Execution Time

4.4 Data Model Performance

As the web-scraping process involves multiple http requests, it consumed 78.3% of execution time; however, transformation and loading into production took 86.8 seconds or only 5% of total execution time. Tracking data model via the performance table allowed to reduce original execution time from 798 seconds.

Stage	Total Seconds	Proportion Time	Files Processed	Files Prop
Load	56.9	14.22%	31	5.21%
Transform	29.9	7.47%	1	0.17%
Stage	313.4	78.31%	563	94.62%
Grand Total	**400.2**	**100%**	**595**	**100%**

Table 3: Model Performance Metrics

4.5 Extended Documentation and Reproducibility

A public Git Repo was created to further document the data structures of the pertinent tables, execution steps, the numerous SQL files used as subqueries, and data reproducibility on the user's end via Github .

5 Geospatial Analysis Methodology

A combination of R, SQL, Python, and QGIS was used to derive our results. The preliminary steps of data processing included using Python to curate the data, visualize the data distribution, and to instantiate an R thread under the python kernel to integrate R's CRAN Package "opendatatoronto" into the pipeline as it was not available in PIP sources. This would allow our group to garner the types of values expected during analysis.

5.1 Python Analysis in Jupyter Notebooks

Python is a versatile programming language that allows users to utilize libraries in analysis and visualization applications. To map out our data in a temporal dimension, functions were used to acquire a day of week and time of day. Having integrated geospatial libraries such as Geopandas, users can handle and manipulate spatial data and conduct spatial operation that can be ported to GIS software. Visualization options using Matplotlib are highly customizable, and offer ways by which the air quality data can be better illustrated.

Pythono libraries used include: pandas, requests, SQLAlchemy, rpy2, wget, beautifulsoup4, Geopandas, matplotlib

5.2 Projecting our Data in Geopandas Utilizing PostGIS and PostgresQL

With our large datasets, SQL formed a foundational part of our underlying analysis. To effectively the collect data insights we intended, a database was created to parse through particular sets of data based off a sequence of filters.
Through the PostGIS extension in PostgresQL, our group was able to curate and project the data structure of the air quality data before further analysis in QGIS. Preliminary steps involved projecting all datasets to UTM Zone 17N (EPSG: 26917) and calculating average AQHI values from a predetermined time and day scale. A buffer was created to capture the impact of local traffic surrounding the air monitoring station. This buffer would take the traffic count stations contained within the polygon and tabulate the average number of vehicles that were going through for each traffic count station.

5.3 Spatial Analysis and Visualization using QGIS

With our preprocessing and data refining completed, QGIS would be used to complete any advanced spatial analyses and final visualizations. It was also an opportunity to overlay any other qualitative datasets our group thought that may play a part in affecting the conditions of AQHI readings around the stations. An initial Kernel Density Estimate was generated to identify the concentration/density of air monitoring stations for Toronto. This was used to infer areas that have discrepancies in coverage. An Inverse Distance Weighting Interpolation was derived to create a continuous spatial coverage of AQHI reading based on neighbouring points.

6 Results

Our analysis of Air Quality Health Index (AQHI) trends using Python-generated graphs and charts revealed significant daily and weekly patterns.

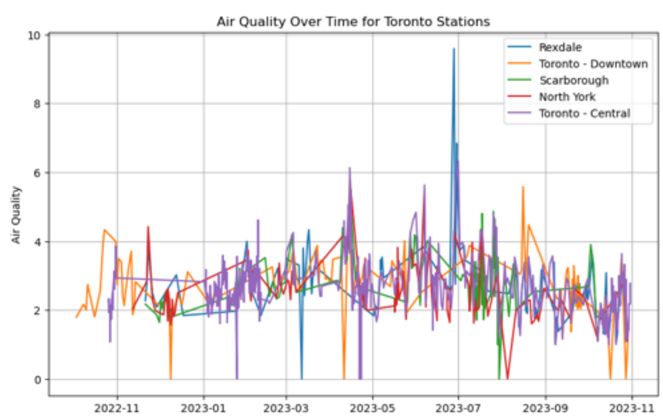

Figure 4: Timeline of AQHI for Data

The overall timeline of AQHI data provided a broad overview of air quality trends over the studied period. The hourly AQHI data exhibited notable fluctuations, aligning with the city's traffic patterns. This suggests a direct correlation between traffic density and air pollution levels at different times of the day. Conversely, the daily AQHI trends showed more consistency, with higher readings observed on weekdays. This indicates a potential cumulative impact of urban activities on air quality over the course of a typical workweek.

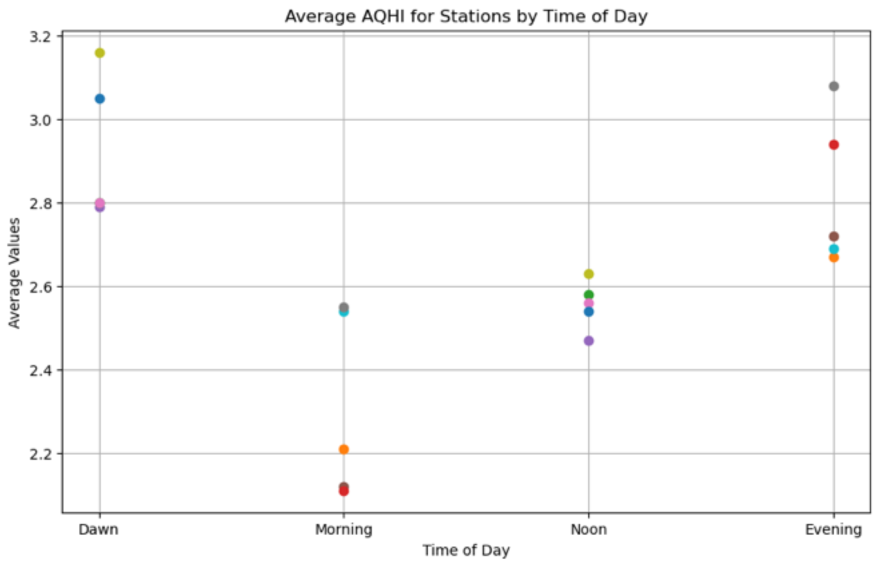

Figure 5: AQHI on Hourly Scale

Spatial analysis utilizing QGIS offered a nuanced view of the relationship between traffic volumes and air quality. The Buffer Analysis for Air Monitoring Stations in relation to Traffic Count Stations indicated a complex spatial distribution of AQHI in connection with traffic density.

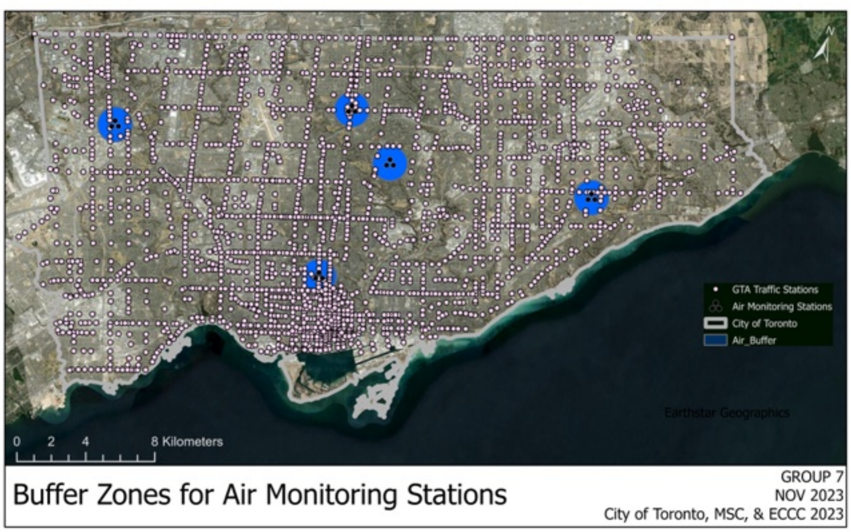

Figure 6: Buffers for Air Stations with Traffic Count Stations.

The anticipated direct correlation between high traffic counts and poor air quality, depicted in Figure 7, was not as straightforward as expected. The Average Traffic Count Buffer analysis and Kernel Density Estimate (KDE) results, shown in Figure 8, suggests a multifaceted relationship.

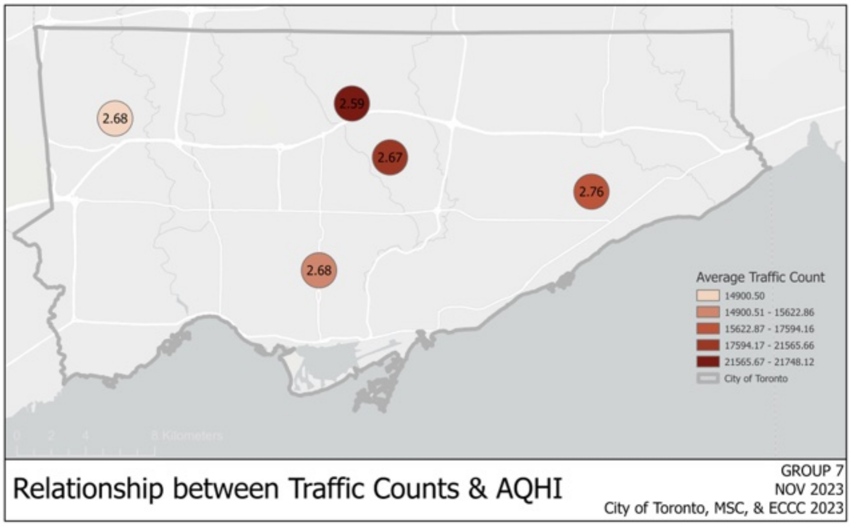

Figure 7: Average Traffic Count Buffer with Labelled AQHI.

This complexity was further supported by the Inverse Distance Weighting (IDW) interpolation,depicted in Figure 9, emphasizing the influence of various environmental and urban factors on urban air pollution.

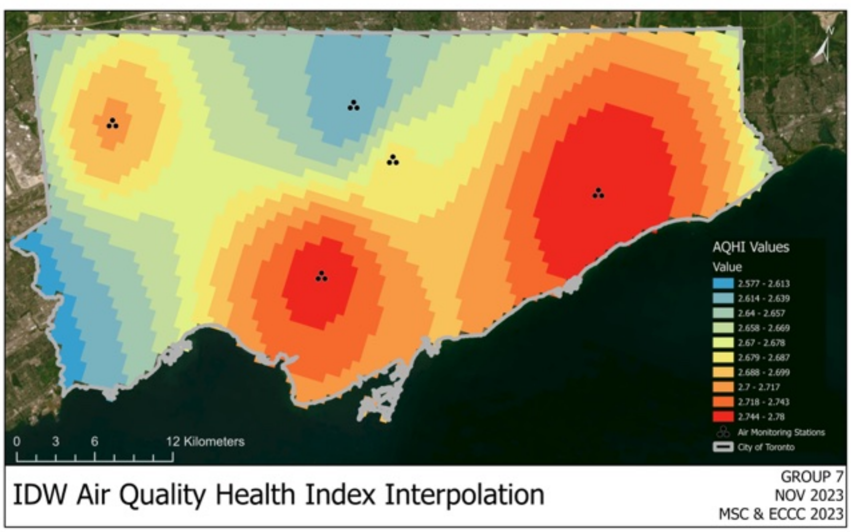

Figure 8: IDW Interpolation

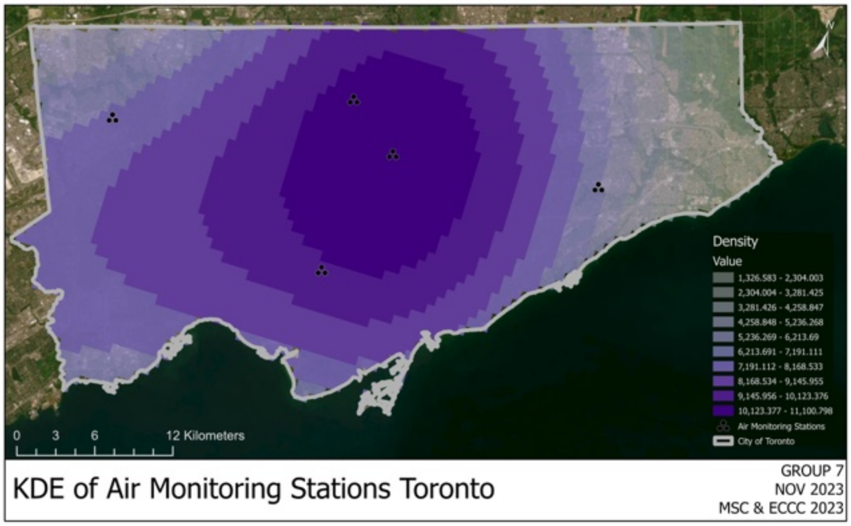

Figure 9: KDE Results

Table 4 depicts a tabular view of the average AQHI values across different air monitoring stations in Toronto and reveals a spatial variability in air quality.Stations in Rexdale, Scarborough, and North York showed moderate AQHI values with minimal daily variation. In contrast, the Toronto-Downtown station reported slightly higher AQHI readings, likely reflecting the effects of increased urban density and traffic activity.

Station ID	**FCKTB Rexdale**	**FCWYG Toronto - Downtown**	**FDQBU Scarborough**	**FDQBX North York**	**FEUZB Toronto - Central**
Average Traffic (buffer)	14900.50	15622.87	17594.17	21748.12	21565.67
Station Average AQHI	2.68	2.68	2.76	2.59	2.67
Dawn Average AQHI	3.05	2.79	3.16	2.8	2.8
Morning Average AQHI	2.21	2.12	2.54	2.11	2.55
Noon Average AQHI	2.58	2.56	2.54	2.47	2.63
Evening Average AQHI	2.94	3.08	2.67	2.72	2.69
Monday Average AQHI	2.67	2.72	3.02	2.65	2.61
Tuesday Average AQHI	2.56	2.4	2.88	2.71	2.71
Wednesday Average AQHI	3.33	2.84	2.92	2.9	2.81
Thursday Average AQHI	2.8	2.77	2.77	2.58	2.7
Friday Average AQHI	2.91	2.82	2.72	2.67	2.73
Saturday Average AQHI	2.23	2.5	2.46	2.42	2.52
Sunday Average AQHI	2.34	2.83	2.54	2.25	2.55

Table 4: Air Monitoring Station Traffic Volume & AQHI Averages

The findings challenge the initial hypothesis of a straightforward, linear relationship between local traffic volume and AQHI readings. Instead, they point to a more complex interplay, where traffic is a significant but not exclusive factor influencing air quality. These results underscore the importance of considering additional factors such as atmospheric conditions and pollutant dispersion in urban air quality assessments.

Temporal analysis further highlighted distinct AQHI patterns in relation to human activities and urban schedules. Lower AQHI values in the morning, increasing towards evening, mirrored the city's traffic peaks. Weekday AQHI readings were consistently higher than weekend readings, aligning with regular workweek patterns and urban traffic flows.

7 Discussion

The general finding of our data reveals that the average local traffic contained within each buffer around the air monitoring stations did not impact the readings as we initially thought. Figure 6 illustrates the non correlated relationship between higher traffic counts and higher AQHI values. We expected that with higher volumes of traffic and vehicular movement, that there would be a higher concentration of urban air pollution, directly increasing the AQHI reading for each monitoring station. These results suggests that perhaps there are more variables at play and factors to consider when running an analysis for a smaller scale study area.

An important notion to consider is that Toronto is surrounded by other large municipalities in the region. Air pollution is not entirely confined to a space or defined boundary, and as such will travel and move according to atmospheric conditions. The dispersion of this air reading will also impact the readings. Ultimately, the simplified AQHI readings at the hourly and daily temporal scales do match with normal expectations respectively. As illustrated in Figures 3, the gradual increase in AQHI follows the working schedule of a typical day. Morning concentrations are comparatively lower and will rise as the level of traffic in the city increases. Values will be highest during the noon/evening as the dispersion from emission sources builds up. As workplace operations and vehicles dwindle down, the air pollution readings will decrease overnight. Figure 4 displays a similar pattern conforming to the work week and level of human interaction with the environment. The typical Monday to Friday schedule displays a higher average reading as compared to the weekend, where traffic counts are considerably composed of recreation or visit to the city. The Toronto - Downtown sees an increase, where tourism/recreation may play a large part.

Again, it is important to consider how the distribution of the existing air monitoring stations affected our results. The KDE map shows that there are implications in using an interpolation map where the are large discrepancies in coverage. As the City of Toronto continues to diversify and grow in population, more services will propagate. To effectively monitor and observe the spatial dispersion of urban air pollution, it may be feasible to identify where potential air monitoring stations may be placed.

7.1 Open Source: Scalability & Reproducibility

Our project focused on creating an application and study revolving around open-source, and collaborative code-sharing. Creation of a GitHub repository and use of open-source autonomous packages with little-to-no hard code, enables us to collaborate on analysis. It was important that a topic like urban air pollution could be linked back to the public, where this information is helpful to the masses. Opening up our methods also contributes to further research where possible. Studies can be conducted at different jurisdictions at different scales.

7.2 Areas of Improvement

As a surface-level exploration of traffic and air quality, the project can incorporate many other qualitative datasets to identify large constituents of air pollution impact. Major points of future improvements include: Enlarging our Study Area: Choosing to focus solely on Toronto introduced edge effects into our study. As aforementioned, air pollution is not defined by a boundary and the study of a smaller scale scope may not explore the variation that may be more apparent in a provincial or national scale study. Comparing other methods of spatial analysis: Conducting iterations of the same analyses can lead to different interpretation of the data. A different approach to interpolation for example, wiih varying sets of parameters will display a contrasting representation, which can effect the translation of data. Incorporating higher level datasets: Including various sources of information can enrich our analysis and reveal more patterns. Using land cover data or remote sensing imagery to overlay the vegetation may uncover the relationship between the natural environment air air pollution. Other datasets can include the use of weather data, and how that may affect readings or the level of traffic around these stations.

7.3 Use of Geospatial Big Data in Air Quality Analysis

In curating the data, this study aimed to create knowledge and wisdom in regards to how sensors can be used in environmental monitoring and assessment. The integration of other datasets offers multiple perspectives in how air quality can impact public health. While informative, large datasets find themselves with interoperability issues. Challenges with harmonizing the datasets will need to be tackled, all the while juggling how existing technology will communicate with newer more advanced frameworks. In the context of geospatial big data, especially in optimizing city services and automation of intelligent technology, there will need to be continual development to ensure that accessibility to this information is not divided.

8 Conclusion

In our analysis, we found that local traffic around air monitoring stations in Toronto did not significantly impact AQHI readings as initially hypothesized. This suggests a more complex scenario where factors like atmospheric conditions and regional influences play a key role. The distribution and coverage of monitoring stations also affected our findings, highlighting the need for a more expansive network to accurately assess urban air pollution. In conclusion, our study underscores the intricate and multifaceted nature of urban air quality dynamics. It highlights the need for a comprehensive approach in evaluating the impact of human activities, particularly traffic, on urban air pollution, taking into account various influencing factors and their complex interrelations.

References

1) Brauer, Michael et al. “Traffic-related air pollution and health in Canada.” CMAJ : Canadian Medical Association journal = journal de l’Association medicale canadienne vol. 185,18 (2013): 1557-8. doi:10.1503/cmaj.121568 *Traffic-related air pollution and health in Canada*. [Canadian Medical Association], [2013].

2) Zhang, Kai, and Stuart Batterman. “Air pollution and health risks due to vehicle traffic.” The Science of the total environment vol. 450-451 (2013): 307-16. doi:10.1016/j.scitotenv.2013.01.074 *Air pollution and health risks due to vehicle traffic*. [The Science of the total environment], [2013].

3) Rossi, Riccardo, et al. “Effect of Road Traffic on Air Pollution. Experimental Evidence from COVID-19 Lockdown.” Sustainability, vol. 12, no. 21, Oct. 2020, p. 8984. Crossref, https://doi.org/10.3390/su12218984. *Effect of Road Traffic on Air Pollution: Experimental Evidence from COVID-19 Lockdown*. [Sustainability], [2020].

4) Ontario Ministry of the Environment, Conservation and Parks. *Air Quality Ontario*. Available at: https://www.ontario.ca/page/air-quality-ontario

5) City of Toronto. (2022). *Traffic Volumes at Intersections for All Modes*. Available at: https://open.toronto.ca/dataset/traffic-volumes-at-intersections-for-all-modes/.