Short-Term Air Pollution Patterns: A GIS Study of $PM_{2.5}$, O_3 and NO_2 Emissions in the Greater Toronto and Hamilton Area, 2024

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GGR444 - Space Time Data Analysis

Course Instructor: Dr. Jue Wang

November 28, 2025

Keywords: Air pollution, Atmospheric pollutants, Urban emissions

Abstract

Rapid Urbanization has led to increasing levels of atmospheric pollution across major metropolitan regions, posing serious risks to both environmental and human health. Fine particulate matter ($PM_{2.5}$), nitrogen dioxide (NO_2), and ozone (O_3) are among the most harmful pollutants influencing respiratory and cardiovascular outcomes over short exposure periods. However, in the Greater Toronto–Hamilton Area (GTHA), not enough is known about short-term fluctuations in these pollutants and how individual mobility shapes real-world exposure. This study investigates how short-term air pollution patterns vary across the GTHA and examines how daily movement contributes to both personal and regional exposure levels. Using hourly pollutant datasets and GPS-based mobility tracks collected over seven days, we applied interpolation methods, time-enabled mapping, and kernel density analysis to identify spatial and temporal hotspots. The space–time interpolation revealed strong daytime patterns in $PM_{2.5}$ and NO_2 concentrations, with peak levels occurring during morning and evening commuting periods across major urban roads, while O_3 concentrations were highest during midday hours. Unmonitored areas between fixed stations experienced pollutant levels comparable to monitored sites, indicating that mobility patterns substantially influence short-term exposure across the GTHA.

1. Introduction:

In recent decades, rapid urbanization has contributed to a significant rise in atmospheric pollution. The growth of industrialization, transportation, and large-scale production has placed increasing pressure on the environment. These activities have resulted in heavy amounts of urban emissions caused by different types of pollutants, which have led to the degradation of the ecosystem while creating respiratory and cardiovascular diseases among humans (Naghan et al., 2022). Among the major pollutants, NO_2 (nitrogen dioxide) is primarily produced by anthropogenic activities. $PM_{2.5}$ is the main contributor to changes in the acidity and alkalinity of precipitation, while O_3, as a major atmospheric oxidant, intensifies environmental disruption and prolongs pollution levels (Liu, 2025). Short-term exposure to $PM_{2.5}$, NO_2, and O_3 can cause airway inflammation and oxidative stress, resulting in an increased risk of hospitalization and death (Mwase, 2025). NO_2 is mostly released through traffic emissions, bus stops, etc., with $PM_{2.5}$ is primarily emitted from vehicle exhaust, industrial combustion, biomass burning, and construction activities (Pültz et al., 2023). Even though O_3 is not directly emitted, it forms in the atmosphere through photochemical reactions involving NO2 and volatile organic compounds released from vehicles, industrial facilities, and solvents (Ren et al., 2022). Given these concerns, we became curious to explore more deeply into the harmful impacts these specific pollutants cause to our health, even in a short period of time. Additionally, we wanted to inquire as to how we, as individuals, may have contributed to the overall Air Quality Index through our regular paths. Understanding these constant problems clearly highlights the urgency to take action towards these exposed communities and neighbourhoods in the GTHA by finding out methods, laying out strict policies, and implementing targeted interventions that can improve the overall quality of life. Air pollution concentrations tend to remain similar for individuals, possibly due to the number of places they visit. Moreover, the level of exposure experienced by an individual directly depends on their activity patterns as it involves the inhalation rate or energy expenditure (Adams, 2016). This study, therefore, investigates how short-term air pollution patterns vary across the GTHA and examines how individual mobility shapes real-world exposure to $PM_{2.5}$, O_3, and NO_2.

2. Methodology:

Flowchart

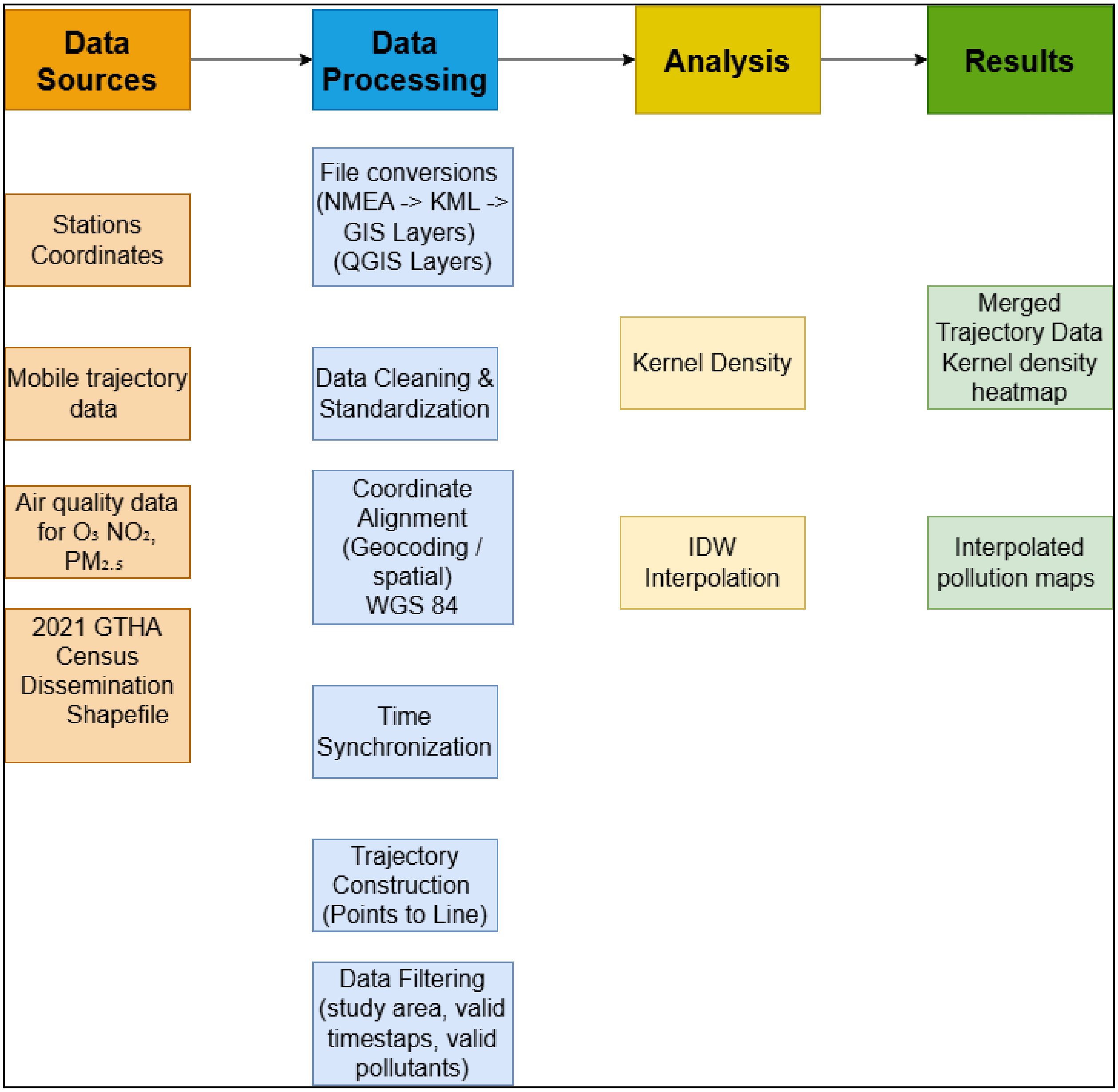

Figure 1. Flowchart of the methods used to conduct the research

2.1 Data Sources

Multiple datasets were used to conduct the analysis. The 2021 Dissemination Area boundary shapefile for the GTHA was obtained from Statistics Canada. This shapefile was used to define the study area and provide spatial context for the exposure analysis.

Hourly air quality data for $PM_{2.5}$, NO_2, and O_3 were collected from the Ontario Ministry of the Environment, Conservation and Parks (MECP) Air Quality Index Historical Database in the format of CSV. The selected study period spans from October 25, 2024, to November 25, 2024, focusing on the GTHA.

In addition to secondary datasets, primary GPS-based mobility data were collected over a continuous seven-day period using each team member's mobile device. The data was collected within the same temporal period as the hourly air quality data to ensure temporal alignment and to support accurate justification of interpolated exposure estimates across the region.

2.2 Data Preprocessing/Processing

Raw GPS trajectory files were initially recorded in NMEA format. These files were imported into QGIS using the NMEA Visualizer and Geo Replay plugins, converted to KML format, and subsequently exported as ESRI Shapefiles for integration into ArcGIS Pro.

All trajectory and air quality datasets were cleaned to remove missing, duplicate, or invalid records. Timestamp formats were standardized to ensure temporal consistency across air quality and mobility datasets, and pollutant attributes were standardized to consistent naming conventions, units, and data formats. To ensure spatial consistency during analysis, all datasets were projected to the WGS 84 coordinate reference system.

An air quality monitoring stations map was created by importing station coordinate data from the Ontario Ministry of the Environment, Conservation and Parks into ArcGIS Pro and converting the tabular data into point features (Figure 1). Stations outside the Greater Toronto–Hamilton Area (GTHA) were excluded. The map of the air quality monitoring stations' locations was used to verify station distribution and identify spatial gaps in monitoring coverage before interpolation.

A trajectory map was generated from the cleaned GPS datasets collected by the team (Figure 2). Individual trajectory points were filtered by study area and valid timestamps, then converted into polyline features using the Points to Line tool to represent continuous movement paths. Distinct symbology was applied to differentiate trajectories by participants. This visualization was used to confirm temporal continuity, spatial coverage, and alignment with the study extent.

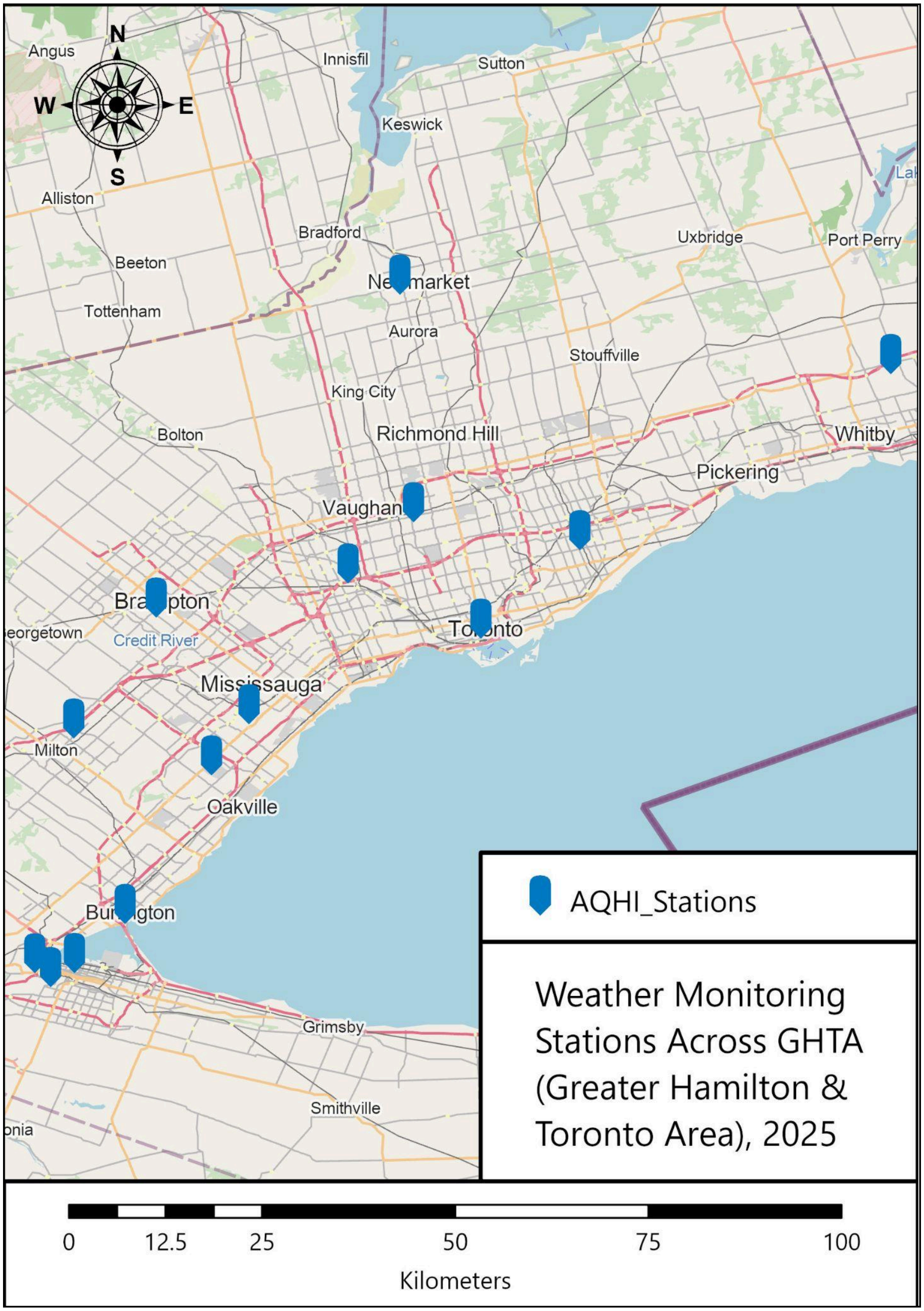

Figure 2. Locations of air quality monitoring stations used to measure hourly pollutant concentrations across the GTHA, 2025.

Figure 3: Map illustrating the complete spatial extent of researchers' trajectories data over one week

2.3 ANALYSIS METHODS

Hourly concentrations of $PM_{2.5}$, NO_2, and O_3 were interpolated using Inverse Distance Weighting (IDW), producing continuous pollution surface maps for each pollutant. These interpolated surfaces allow estimation of air quality at locations between monitoring stations and capture short-term variability throughout the study period.

To examine the mobility patterns, Kernel Density Estimation (KDE) was applied to the trajectory data of each member to identify areas with high concentrations of movement. The resulting density surfaces highlight frequently travelled zones of prolonged activity for each member. Then, each member's kernel density estimation output was merged to generate a composite mobility density surface, capturing the combined spatial extent and intensity of movement across all participants during the study period.

Finally, the interpolated pollution maps were spatially compared with the merged trajectory kernel density output to assess how daily movement patterns intersect with areas of elevated pollutant levels. This approach allows for the evaluation of both regional pollution patterns and individual exposure patterns in the GTHA.

3. Results

Figure 4. a: Inverse Distance Weighted (IDW) map of fine particulate matter(PM 2.5) concentrations in the GTHA with merged total trajectory data for all group researchers during the one-week study period

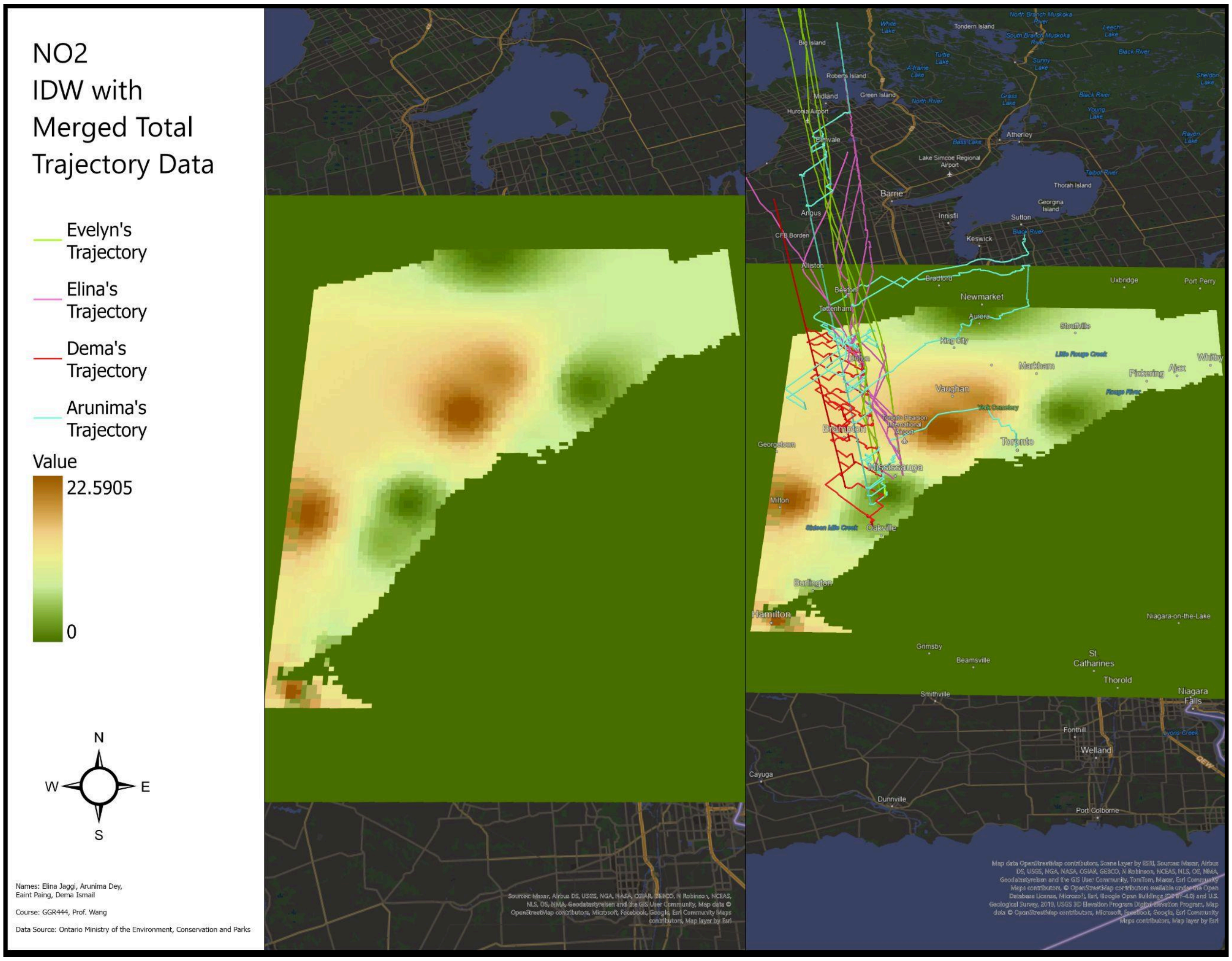

Figure 4.b: Inverse Distance Weighted (IDW) map of nitrogen dioxide (NO2) concentrations in the GTHA with merged total trajectory data for all group researchers during the one-week study period

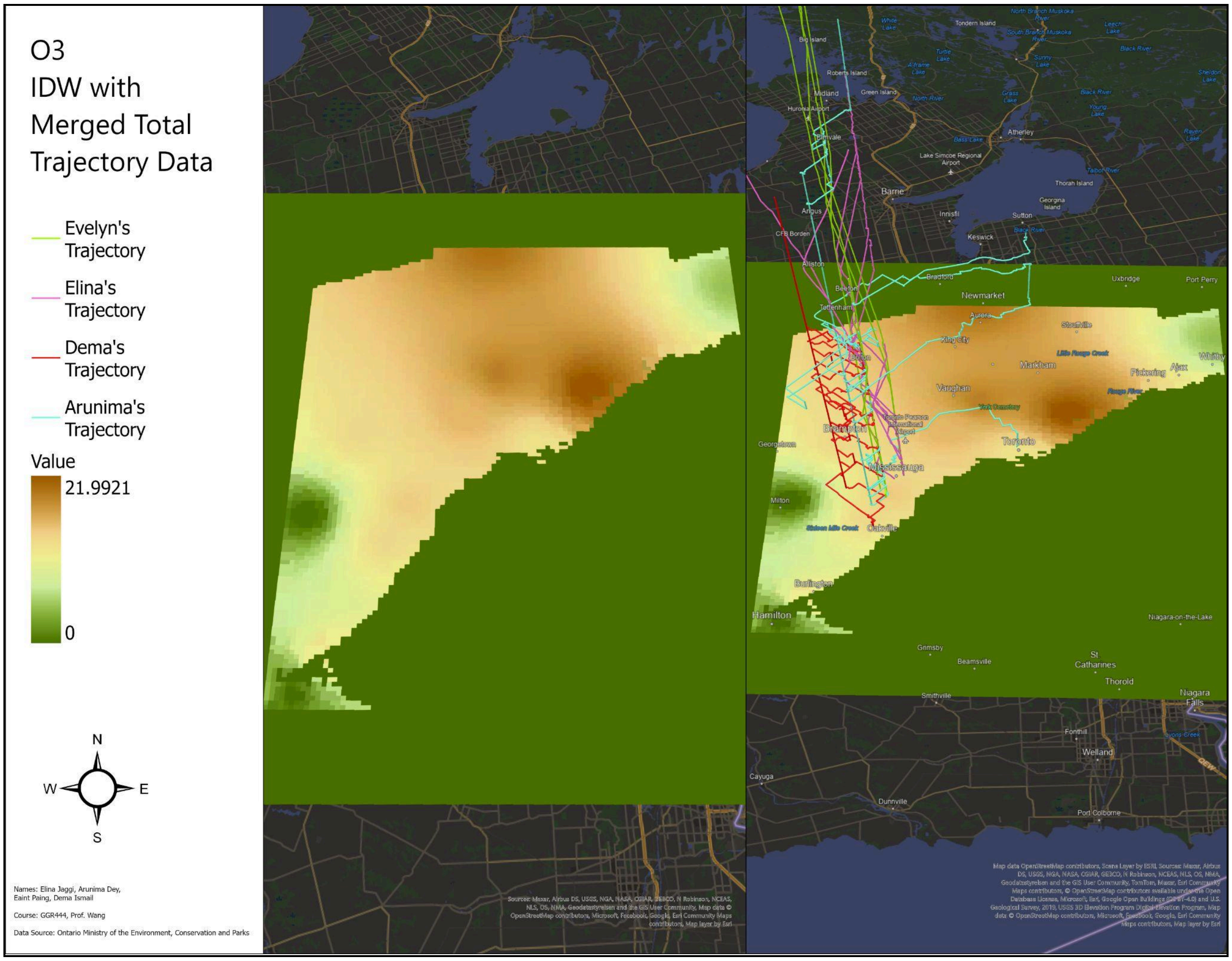

Figure 4.c: Inverse Distance Weighted (IDW) map of ozone (O3) concentrations in the GTHA with merged total trajectory data for all group researchers during the one-week study period

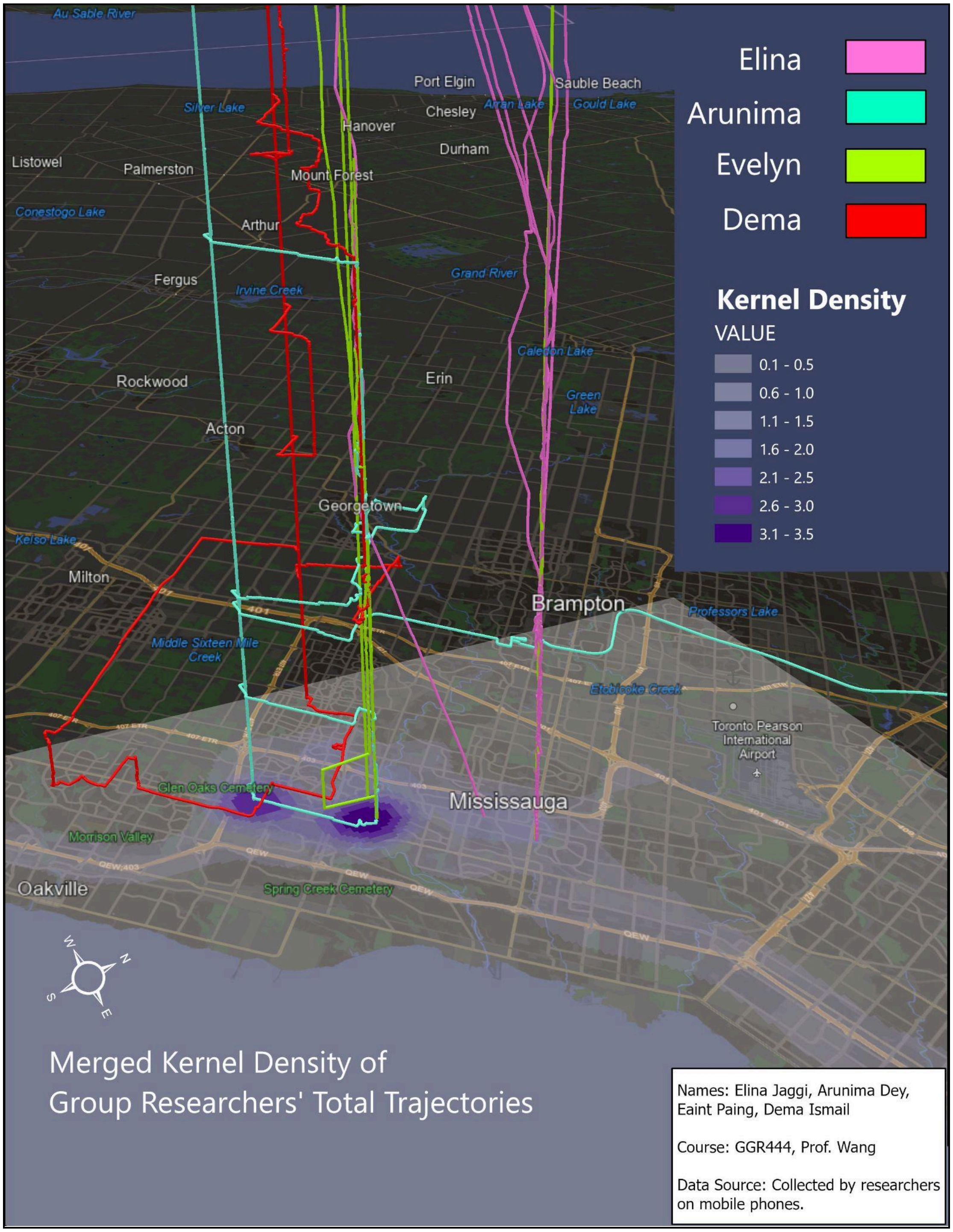

Figure 5: Merged kernel density output of all participants' weekly trajectories, highlighting areas of concentrated movements across the GTHA

Figure 4. a clearly shows that the participants have constantly been in the low PM2.5 concentration area, indicating that the Air Quality and Weather stations in Mississauga measured low amounts of PM2.5. This implies that, unlike Toronto and parts of Hamilton, Mississauga does not have a high amount of PM2.5, which aligns with the high presence of traffic, infrastructure NO2, and industrial emissions that release heavy metals like Pb and Se (Celo, 2021). Even though the data collected by the participants and the overall Air Quality Data were not at the exact same time, but in a similar timeframe, which shows that the participants were not getting much exposed to PM2.5 while they were collecting the data. However, while observing Figure 4.b, it can be inferred that NO2 concentrations in Mississauga are not very low; in fact, they are in the higher range. This explains that even though Toronto and Hamilton tend to have higher PM2.5, Mississauga also consists of a large amount of NO2, possibly due to heavy traffic reasons, which could be a common reason for a Metropolitan city to emit this gas (Requia, 2021). Hence, this indicates that there is a very high chance that the participants were in a heavily polluted environment caused by NO2 in Mississauga. Similarly, Figure 4.c illustrates that the majority of GTHA are very highly exposed to O3. There are many days in GTA where the O3 levels tend to appear more than the standard, which possibly could be due to annual variability in weather that results in changes in the precursor emission rates (Pugliese, 2017) This indicates that out of all three gases, O3 is most abundant in the entire region, highlighting how the participants were consistently exposed to it while being in both Toronto and Mississauga.

The merged kernel density surface (Figure 5) reveals the spatial clustering of participant mobility within the GTHA, with the highest density values concentrated around the University of Toronto Mississauga (UTM) campus. This pattern reflects repeated and prolonged presence in this area, as all participants are students whose daily routines are centered on the campus environment. Additional zones of elevated density are observed along major transportation corridors connecting UTM to surrounding urban areas, indicating frequent commuting activity. In contrast, peripheral regions have lower density values, reflecting limited or transient movement. These results demonstrate that mobility and, consequently, potential exposure are spatially uneven and strongly shaped by shared activity spaces associated with student life.

4. Limitations

To prepare the datasets, several preprocessing steps were performed. First, all GPS files were converted from NMEA format to KML, GPX, and CSV file types to enable compatibility with ArcGIS Pro. However, during the constant conversion of the files, there were some data limitations beyond our control - all of the free converters online were unavailable to take in NMEA file type in the first place, aside from one requiring a subscription beyond 3 file uploads. Therefore, we had to use QGIS plugins to fix it. Finally, the KML files were then imported as XY event layers, allowing the GPS coordinates to be visualized and processed as point features. This process took longer than expected and limited some of the methodology.

Another limitation within this study was related to data privacy. Due to time constraints, we were unable to conduct geomasking, which is a process that obscures or displaces precise location points to protect individual identities. Incorporating geomasking would have allowed for a more secure representation of individual mobility patterns without compromising the integrity of the dataset.

Besides, we couldn't do the geomasking due to time constraints, and the process needed way more technical skill than we expected. While we were working on the interpolation, we kept getting the error "output extent invalid" over and over. We tried testing it with small values like 2 and 3, and larger ones like 300 and 500, but nothing worked. Because of that, we ended up running the IDW using our original point data, even though our original plan was to run the IDW on our visualized 3D dataset.

5. Conclusions

Through Figure 4, it can be clearly inferred that by using the Kernel Density that the team members, i.e., participants, have predominantly been around the same area within the GTHA. The areas that can be highlighted are the Ridgeway, Square One, and the University of Toronto, Mississauga region, indicating that the participants were mostly around their home or near their university.

In conclusion, our research indicates that air pollution patterns in the GTHA, especially in the short term, vary greatly in terms of both space and time. That's why the way individuals travel around the region is important to understanding these variations. The analysis of the kernel density map highlights that our cohort encompassed a relatively similar activity space throughout the week, predominantly in the Ridgeway, Square One, and UTM areas of Mississauga, thereby linking our overall exposure to the level of pollution associated with the communities mentioned above. Further analysis via IDW demonstrated that Mississauga recorded significantly lower levels of PM2.5 than did the cities of Toronto and Hamilton, reflecting the well-documented correlation between PM2.5 levels and traffic and industry levels. Our analysis suggests that, while our PM2.5 levels were relatively low near our weekly routes, NO2 levels were elevated due to the presence of busy urban street/highway systems, transit bus routes, and commuting corridors. Ozone exhibited a contrasting trend relative to PM2.5 levels as it was elevated in less populated, non-industrialised areas, and is supported by scientific data regarding ozone formation in the atmosphere.

By comparing pollution maps with our trajectory density map, we were able to identify where pollution levels overlapped with individual daily movements. Through this analysis, we found that where an individual works and lives, how long they were there, and how often they travelled through a specific area also affect individuals' exposure to air pollution in the Greater Toronto and Hamilton Area (GTHA). Thus, even a small study has demonstrated that mobility had a clear influence on the pollutant levels each of us encountered.

Despite facing some challenges, including time constraints, file conversion issues, and uneven station coverage, our research continues to highlight the importance of combining hourly pollution data with mobility data. The combined datasets provide a more accurate picture of a person's short-term exposure to pollution and reveal significant local variations in comparison to the monitoring stations alone. As a result of our research, considering the impact of mobility when developing public health interventions in the GTHA will be beneficial to improve the quality of life of our residents.

Through the inclusion of our own data, we were able to discover the specific gases specific gases we are thr most exposed to which provides us more insights about out our own health by knowing the type of air we are breathing. In future, this type of analysis involving personal data collection can help individuals understand more about the type of environment they live in and how the data could help the concerned authorities living in the area to get a more structured idea about making it better for the residents living there.

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