



The
University
Of
Sheffield.

Department of
Automatic Control &
Systems Engineering

Application of Statistical Analysis Methods to Determine the Changes in Traffic Flow Rate, Pollutant Level, and Peak Time Patterns in the city of Sheffield: Prior and Post-COVID-19 Pandemic Perspectives

Zaid Daghash

May 2024

Supervisor: Dr. Giuliano Punzo

**A dissertation submitted in partial fulfilment of the requirements for the degree of
BEng Computer Systems Engineering.**

Abstract

The COVID-19 pandemic has had a rather significant impact on certain aspects of daily life. Most notably, it changed how we commute and at what times we choose to commute. The problem under investigation is how the pandemic has altered the rate of vehicle traffic, the commuting times, and the levels of pollutants in the city of Sheffield. The results of this research will help law makers to better prepare if challenged with a similar crisis in the future.

Goenaga *et al.* [1] and Gao and Levinson [2] have both produced comparison graphs in order to help visualise the changes in traffic patterns. The authors of [1] also used descriptive statistics and percentage changes in order to assess the changes in traffic patterns. Whereas the authors of [2] used various mathematical equations and regression analysis to assess the changes. In this research, comparison graphs were used to help visualise the changes in traffic patterns, the changes in peak times, and the changes in the levels of pollutants. Descriptive statistics accompany the graphs to provide more details. Hypothesis testing was also utilised in order to determine whether there is any significant changes in the data sets. Finally regression analysis was carried out to help establish the relationship between the concentration of the pollutants and the traffic volume.

According to the results of the hypothesis testing, there is a difference between the traffic flow rate data in 2023 and 2019. The Centre and the North of Sheffield witnessed on average an increase by 4.5% and 1.3% respectively in traffic flow rate. Whereas the West, South, and East witnessed a decrease in traffic flow rate by 23.4%, 3.3%, and 2.6% respectively. The North and Centre regions had a noticeable increase in the median traffic flow rate (11.1% and 20% respectively), whereas the South and the West experienced a significant decrease in the median traffic flow rate (11.1% and 60% respectively). The East region witnessed no change in the median traffic flow rate. The West, South, and North regions had minor changes in the variation of the traffic flow rate, whereas the Centre region experienced an increase of 24.1%, and the East witnessed a decrease by 11.6% in the variance. The South, Centre, and the East regions had changes in the standard deviation, indicating that there has been changes in the spread of traffic flow rate data.

According to the significance levels between the data sets, the peak times had minor changes overall across the morning and afternoon periods. The average timing of the morning peak had shifted backwards in the North, South, East, and West by 3.8%, 2.3%, 3.9%, and 21.7% respectively. The median morning peak times remained the same in the North, East, and West of Sheffield, whereas the

South region had a minor backwards shift by 5%. The variance and standard deviations had increased significantly in the North, East, and West regions, with the South region being unchanged. This indicates that there has been major changes in the spread and variability of the morning peak times. The average timing of the afternoon peaks had shifted forwards by 1.3% in the North, whereas the other locations saw very minor backward shifts. The median, variance, and standard deviation of the afternoon peak times were similar to those observed in the morning.

The hypothesis testing has confirmed that there has been a noticeable change in the levels of NO₂ between the years 2019 and 2023. Interestingly there is no noticeable change in the levels of PM_{2.5} and PM₁₀. The levels of PM₁₀ remained constant, whereas the levels of PM_{2.5} increased by 6.9%, and the levels of NO₂ decreased by 50%. The models built for predicting the concentrations of NO₂, PM₁₀, and PM_{2.5} have indicated that the traffic flow rate did not have an impact on the concentration of these pollutants, and third order models have also indicated that there is no relationship between the traffic flow rate and the concentration of these pollutants.

These results suggest that the rate of inbound traffic (North and South) has changed slightly, and the rate of outbound traffic (West and East) has had a noticeable change. There has been a backwards shift in the morning peak times across all regions but most significantly being the West. On the other hand, the shifts in the peak times in the afternoon period have been very minor across all regions. Emissions of pollutants have either gone down or remained the same, however according to the results of the regression analysis, there is no evidence to suggest that the traffic volume was the leading cause in these changes.

Individual Contribution

The entirety of the work done that led to the completion of this project was done by myself (Zaid Daghash). This includes writing code to carry out calculations, hypothesis testing, regression analysis, and plotting graphs. The traffic flow rate data was obtained from the Urban Flows Observatory portal [3]. The Air Quality Index (AQI) data was obtained from the dedicated website for the Devonshire Green air quality station [4]. The weather data was obtained from the dedicated website for the weather station located in the Centre of Sheffield [5]. For code writing, the MATLAB software was used [6], and for the peak time ‘box and whisker’ figures, the GraphPad Prism software was used [7]. The Gantt chart found in [Appendix 2](#) was produced online and then exported as a Microsoft Excel Worksheet [8]. The entirety of this report was written by myself using Microsoft Word [9].

Acknowledgments

I would like to express my sincere gratitude to Dr. Giuliano Punzo for his mentorship and guidance throughout this project. I am thankful to Dr. Rob Ward for his insightful feedback and constructive criticism which greatly enriched the quality of my work. I am indebted to my family members for their support and encouragement during this challenging academic year. Finally, I extend my heartfelt appreciation to all those who have played a part, no matter how big or small, in the completion of this dissertation. Your support and encouragement have been invaluable to me throughout this journey.

Table of Contents

1. Introduction.....	1
1.1. Aims & Objectives.....	1
1.2. Background & Motivation.....	1
1.3. Project Management.....	2
1.4. Overview of the Report.....	2
2. Literature Review.....	3
2.1. Impact of New Policies on Vehicle Traffic Patterns.....	3
2.2. Impact on Road Safety.....	8
2.3. Environmental Impacts.....	8
2.4. Methods Used.....	9
2.5. Summary.....	12
3. Methodology.....	14
3.1. Data Gathering.....	14
3.2. Comparison Plots.....	15
3.3. Analysis of Traffic Flow Rate Data	15
3.4. Analysis of Peak Times.....	16
3.5. Regression Analysis.....	16
4. Results.....	17
4.1. Changes in Traffic Patterns.....	17
4.1.1. Paired t-tests.....	20
4.1.2. Descriptive Statistics.....	21
4.2. Shifts in Peak Times.....	23
4.2.1. Descriptive Statistics.....	28
4.3. Changes in the Levels of Pollutants.....	29
4.3.1. Paired t-tests.....	30
4.3.2. Regression Analysis.....	31
5. Discussions & Conclusions.....	39
5.1. Limitations.....	41
6. References.....	43
7. Appendix 1 – Work Breakdown Structure.....	47
8. Appendix 2 – Gantt Chart.....	48
9. Appendix 3 – Percentage Change Between the Descriptive Statistics (Peak Times).....	49

1. Introduction

1.1. Aims & Objectives

The main aim of this project is to investigate whether there has been any noticeable changes in the levels of traffic and the times at which people choose to commute as a result of the COVID-19 pandemic in the city of Sheffield. The secondary investigation of this project includes looking at how the changes in traffic volume have impacted the environment and the emissions of toxic gasses in the city of Sheffield.

The following objectives were achieved to meet the goals of this project:

1. Visualise the average traffic flow rate in the years 2019 and 2023.
2. Conduct hypothesis testing on the traffic flow rate data sets.
3. Determine the descriptive statistics for the traffic flow rate data sets.
4. Visualise the distribution of the peak times in the morning and the afternoon hours.
5. Determine the significance between the peak time data sets (computing the p-values).
6. Determine the descriptive statistics for the peak time data sets.
7. Visualise the Air Quality Index (AQI) data sets.
8. Conduct hypothesis testing on AQI data sets.
9. Build regression models for predicting the AQI of certain pollutants.
10. Using the regression models, study the effects of traffic flow rate on the AQI values.

1.2. Background & Motivation

As of 2021, Sheffield's population stood at 552,698 [\[10\]](#). Being situated in a mountainous region, Sheffield's land mass is filled with rivers, valleys, and hills. The city's infrastructure is well-developed, containing a network of cycling routes, roads, and government funded transportation systems. The city also has a series of major motorways which provide access to other cities in the country. Similarly to other urban cities, the city of Sheffield occasionally witnesses traffic congestions during the peak times. These congestions therefore lead to negative environmental impacts such as bad air quality. The government has plans set in motion in order to improve the traffic flow by promoting the use of public transport and upgrading the current infrastructure. The results produced by this research will therefore provide a guide for policy makers on how to mitigate congestions during peak times, and how to improve the air quality in the city.

1.3. Project Management

In order to best manage this project and ensure that its main objectives were met, the project was divided into several stages. The initial stage involved conducting research about the topic and gathering data. This includes literature review and obtaining traffic, AQI, and climate data. To get an initial view on how the traffic and air quality data has changed, several comparison plots were produced. The next stage was to then write the interim report which showcased the current work progress. Next, data analysis began by determining the descriptive statistics (mean, median, variance, standard deviation) of the traffic flow rate data and the AQI data. Hypothesis testing was then carried out in order to determine if the difference between the data sets was significant or not (this was done for both traffic flow rate data and AQI data). Descriptive statistics were also determined for the peak times in order to classify the type of shifts observed. Regression analysis was then carried out in order to assess how the concentrations of certain pollutants have changed, and if the traffic flow rate had contributed to the presence of these pollutants. Once the technical work was done, the next stage was to write the dissertation using the relevant reviewed literature, the results, and the conclusion as the main body. Finally, PowerPoint slides which summarise the information given in the dissertation were created, ready to be presented on the specified date.

To see how the project was managed in more detail, please refer to the Work Breakdown Structure (WBS) and the Gantt chart available in appendices [1](#) and [2](#).

1.4. Overview of the Report

The first main chapter of this report is the [Literature Review](#). The literature review explores the ideas and results of several sources based on the impact of new government policies, the impact on road safety, the impact on the environment, and the methodologies used. The literature review will serve as an explanation to why this research is important and what areas require further research, hence being the motivation for this project. The [Methodology](#) section presents the approaches taken in order to assess the changes in traffic patterns and their impact on the environment, and therefore the [Results](#) section displays the findings as a result of applying these approaches. Finally the [Discussions & Conclusions](#) section then discusses the significance of the results and why these results were achieved, and point to the limitations that were presented upon undertaking this project.

2. Literature Review

The COVID-19 virus has massively impacted daily life [11]. With educational institutions opting for online teaching methods [12], restaurants opting for contactless delivery options [13], the closure of small businesses [14], and employees conducting their work from home [15]. Most notably, the pandemic has drastically impacted the traffic volume observed at all times throughout every single city across the globe. With the government enforcing curfews after which there should be no casual mobility [16], and setting limits to how many people can be present at a specific location at a given time. Therefore witnessing a tremendous decline in vehicle traffic movement was fully expected. Many publications have conducted research concerning the impact of the COVID-19 pandemic on vehicle traffic. The following are key questions for discussion in the literature:

- What were the policies set by the government that caused a decline in traffic volume? And how did they affect commuting behaviours?
- How did employees conducting their work from home impact commuting patterns? And was a shift observed in the commuting times?
- How did the pandemic impact mobility? And subsequently how did this impact the environment?
- What were the methods used that enabled the analysis of the changes in traffic volume?

It is important to identify the key findings observed in relevant publications, how they compare to the findings observed in other publications, and which areas require further research.

2.1. Impact of New Policies on Vehicle Traffic Patterns

As mentioned in the [Abstract](#) section of this report, with the outbreak of the pandemic and the rising fear of contracting the disease, it was only a matter of time before governing bodies began setting policies to minimise the spread of the disease. With these policies set in place, vehicle traffic volume was bound to decrease. The states of Virginia and North Carolina witnessed a noticeable decline in traffic volume once social restrictions were set in motion. This can be seen in [Figure 1](#).

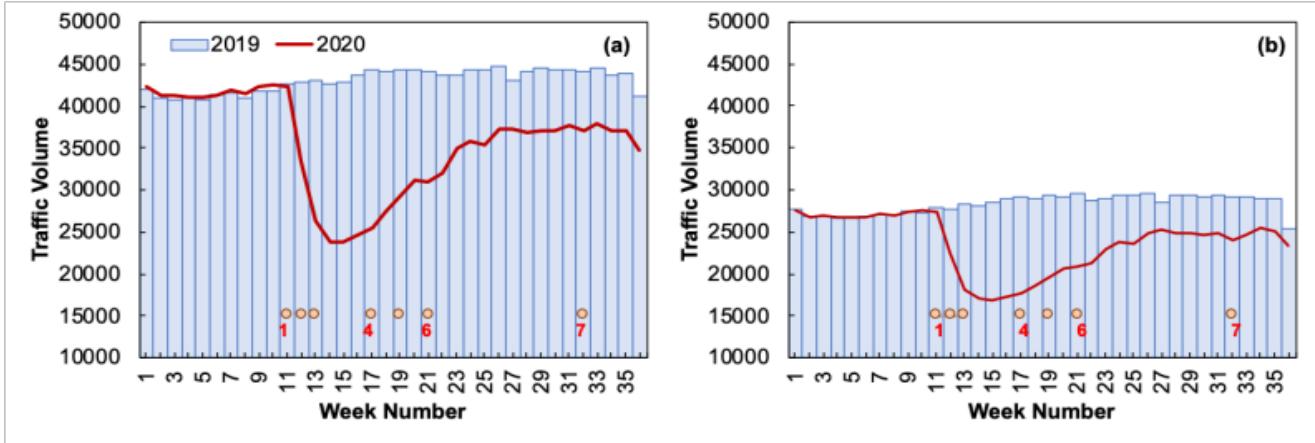


Figure 1: Traffic volume observed in the states of North Carolina (a) and Virginia (b) [1, Fig. 1].

In week 11, the governing body of the state of North Carolina has announced that social gatherings of more than 100 people was banned. In the same week, the state of Virginia began the closure of educational institutions [1, Table. 2]. The result of these actions caused a vast decline in traffic volume in both states. This decline can be visually observed after the passing of week 11 in [Figure 1](#). The states of North Carolina and Virginia began to slowly ease the restrictions set in place in weeks 19 and 22 respectively [1, Table. 2]. The slow incline of traffic volume in both states can be observed after the passing of those weeks in [Figure 1](#). During the period in which social restrictions have been imposed, it has been noted that the volume of vehicle traffic has reduced by an average of 39% and 40% in the states of North Carolina and Virginia respectively.

Although the data presented does give an insight into how traffic volume was impacted during the pandemic in comparison to the traffic volume observed in the year 2019, one more data set is missing which is the data set that represents the traffic volume after the restrictions have been removed (e.g. the year 2021). It is essential to compare the ‘before’ and ‘after’ data sets in order to identify if there has been any long-lasting effects on traffic volumes after the departure of the pandemic.

Similarly to the states of North Carolina and Virginia, the department of transportation in the state of California monitored the traffic flow rate across the morning period in several cities in the years 2018, 2019, 2020, and 2021. This can be seen in [Figure 2](#).

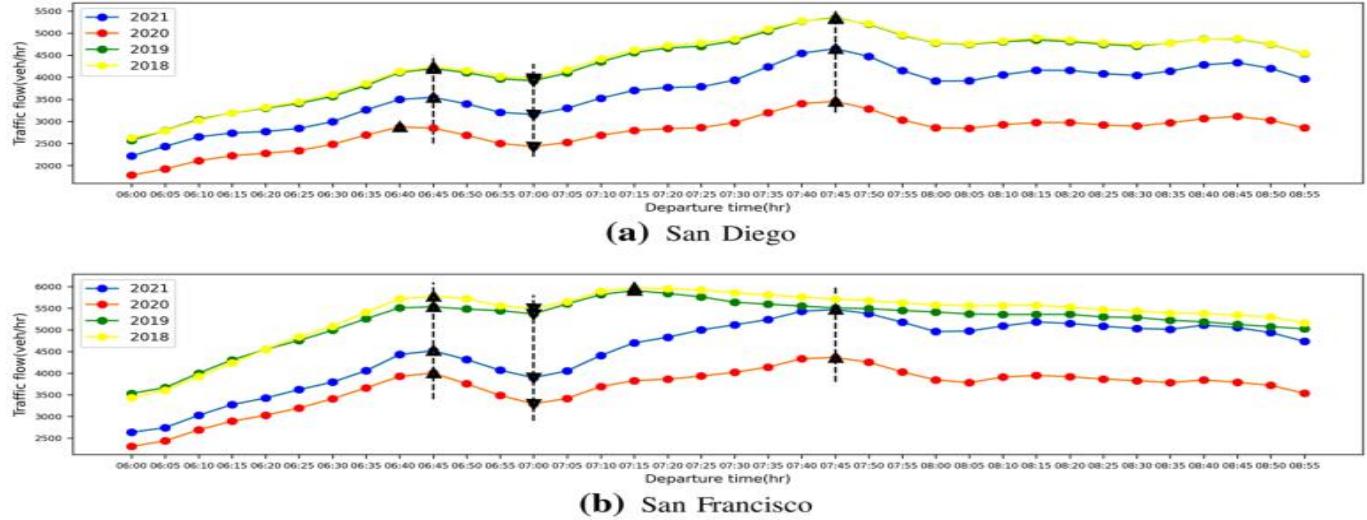


Figure 2: Traffic flow rate observed in the cities of San Diego (a) and San Francisco (b) [2, Fig. 4].

One of the interesting side effects that has been observed in vehicle traffic patterns after the introduction of the COVID-19 pandemic is the ‘Double-Humped’ phenomena. The phenomena describes the appearance of two periods of time where the vehicle traffic is at its maximum (peak) during the morning hours. [Figure 2](#) shows that the two peaks maintained their positions throughout the years 2018, 2019, 2020, and 2021 in the city of San Diego. Whereas in San Francisco, the second peak in the years 2020 and 2021 has shifted to the right. This indicates that the pandemic hasn’t altered commuting times in the city of San Diego. However, due to a shift in the peaks during the pandemic (2020) and after the pandemic has subsided (2021) in the city of San Francisco, it is evident that the pandemic has also altered commuting times. It is also interesting to note that after the pandemic has subsided in both cities, the traffic flow rate level hasn’t returned to a level of known norms (as observed in the years 2018 and 2019), hence this shows that the pandemic has long-lasting impacts on vehicle traffic volume.

The investigation concluded that the reason why the ‘Double-Humped’ phenomena occurred was due to the fact that employees from different sectors chose to commute at different times of the day during the pandemic. As stated before, the government enforced new laws to help limit the spread of the disease. Due to the enforcement of these laws, 70% of employees globally were said to be working from home [\[17\]](#). Due to a high volume of employees working from home, employees from different sectors travelled to their onsite working environment on different days and on different times. This meant that the type of

employees travelling to work has changed due to the introduction of remote working. This in turn caused the “emergence of two well defined peaks” [2, p. 1] in the traffic flow rate curve during the morning hours. This is supported by Tables 1 and 2.

Table 1: Composition of commuting employees before the pandemic (2019) in the state of California. Reproduced from [2, Table. 4].

<u>Industry</u>	<u>Commuting time (hr)</u>	<u>Number of commuters</u>
<i>Natural resources and mining</i>	7:06	23,582
<i>Utilities</i>	7:08	49,962
<i>Agriculture, forestry, fishing and hunting</i>	7:09	20,876
<i>Construction</i>	7:15	396,447
<i>Manufacturing</i>	7:15	740,299
<i>Transportation and warehousing</i>	7:15	360,725
<i>Wholesale trade</i>	7:19	363,564
<i>Educational services</i>	7:22	658,011
<i>Administrative and support services</i>	7:25	524,548
<i>Health care and social assistance</i>	7:26	1,385,880
<i>Accommodation and food services</i>	7:26	918,595
<i>Finance and insurance</i>	7:27	288,023
<i>Other services, ex. Public admin</i>	7:27	313,631
<i>Retail trade</i>	7:30	833,694

Table 2: Loss of commuters after the arrival of the pandemic (2020) in the state of California. Reproduced from [2, Table. 5].

<u>Industry</u>	<u>Commuting time (hr)</u>	<u>Commuters loss</u>
<i>Natural resources and mining</i>	7:06	7,132
<i>Utilities</i>	7:08	18
<i>Agriculture, forestry, fishing and hunting</i>	7:09	2,729
<i>Construction</i>	7:15	81,212
<i>Manufacturing</i>	7:15	187,560
<i>Transportation and warehousing</i>	7:15	62,841
<i>Wholesale trade</i>	7:19	208,460
<i>Educational services</i>	7:22	558,115
<i>Administrative and support services</i>	7:25	196,541
<i>Health care and social assistance</i>	7:26	337,376
<i>Accommodation and food services</i>	7:26	320,560
<i>Finance and insurance</i>	7:27	220,183
<i>Other services, ex. Public admin</i>	7:27	145,709
<i>Retail trade</i>	7:30	185,259

The research carried out by Goenaga *et al.* [1] and Gao and Levinson [2] have the following similarities:

- Both studies provided descriptions backed up by statistical analysis on how the pandemic affected the volume of traffic in different parts of the United States of America.
- Both studies agree that policies set by the government played a vital role in determining the level of traffic volume.

However, the study conducted by Goenaga *et al.* focused on the changes in the levels of vehicle volume during and before the pandemic only. Whereas the research carried out by Gao and Levinson gave an insight into the lasting effects of the COVID-19 pandemic on vehicle traffic volume by comparing pre-pandemic and post-pandemic data sets, as well as highlighting an interesting side effect of the pandemic ('Double-Humped' phenomena).

2.2. Impact on Road Safety

Different researchers had contradicting opinions on the pandemic's impact on road safety. A study conducted in the United States of America has concluded that motor accidents have increased during the pandemic, and the reason why was due to an increase in drivers' carelessness and erratic driving behaviour [18]. Another study conducted in Spain concluded that there has also been an increase in motor accidents during the pandemic, where the reasoning behind the increase was due to the majority of the public opting for driving their own personal vehicles instead of using modes of public transportation [19]. However, studies conducted in other countries stated that the pandemic has positively impacted road safety. Studies conducted in Nepal, India, Brazil, Cyprus, Saudi Arabia, and Greece have concluded that motor incidents (and any injuries related to motor incidents) have decreased during the pandemic and that was due to the enforcement of lockdowns and restricting social interactions [20]-[22].

Due to the presence of differing opinions on whether road safety had improved or not during the pandemic era, it is impossible to conclude whether the pandemic was a decisive factor behind the improvement or decline in road safety. However, any improvements seen in motor accidents, injuries, and fatalities during the pandemic, can be heavily attributed to the decreased levels of traffic volume due to the enforcement of restrictions on mobility [20]-[28].

2.3. Environmental Impacts

Without a shadow of a doubt, the pandemic had a massive impact on the environment. After restrictions have been enforced, there have been observations being made which indicate a reduction of air pollution and greenhouse gases [29]. It has been reported that there has been a near 50% reduction in carbon monoxide and nitrogen oxide emissions after manufacturing industries have been shut down in China [30], as well as a 50% reduction in polluting gases present in the air in the city of New York [31]. According to [32], nitrogen dioxide is formed due to the process of combustion that takes place after a vehicle's engine has been ignited. Nitrogen dioxide is a harmful gas since it weakens the lungs, and thus "aggravates asthma" [33]. During the lockdown period, the city of Madrid has witnessed a reduction of 43% in the concentration of nitrogen dioxide present in the atmosphere compared to the same time period in the years 2016-2019, as well as a 35% reduction after the restrictive procedures have been lifted when compared to the same time period in the years 2016-2019. This can be seen in [Figure 3](#).

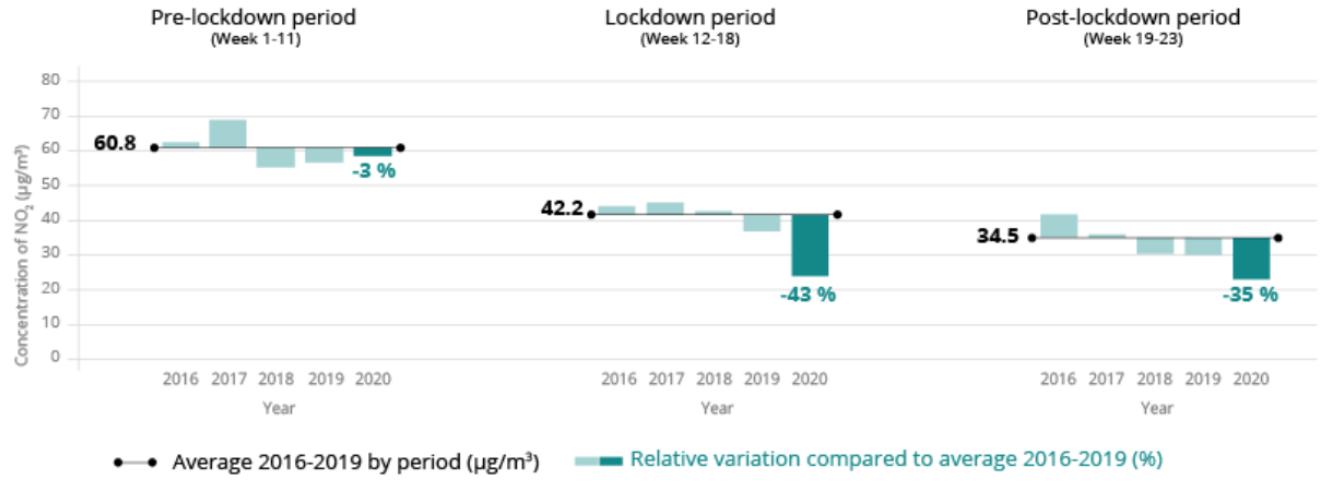


Figure 3: Concentration of nitrogen dioxide observed in the atmosphere in the city of Madrid in the years 2016 - 2020 [34, Fig. 3].

Even though many sources agree that a lot of regions have witnessed a large improvement in air quality throughout the pandemic, Chris Jones, a researcher at the Met Office, stated that while a 7% reduction in emissions is unheard of, 93% of emissions are still present in the atmosphere during the lockdown phase [35]. He also stated that toxic pollutants like carbon dioxide have a long lifespan in the atmosphere, and any alterations to the rate of gas emissions will have little to no effect on the concentration of carbon dioxide in the atmosphere [35].

2.4. Methods Used

With regards to analysing the changes in traffic patterns, Goenaga *et al.* [1] compared the traffic volume throughout the working days and excluding the weekend across a 13-week period from data sets obtained before the pandemic (2019) and during the pandemic (2020). The authors proceeded to group the traffic volume data points from each day into clusters. The most congested cluster would be identified, and then the centroid of that cluster would be determined. That centroid will then be used to represent the traffic volume for that given day. The number of clusters was computed using the Elbow method [36]. The authors proceeded to compute the percentage change in traffic volume between the two years. This is shown in equation (1).

$$\%Change = \frac{\text{Traffic}2020 - \text{Traffic}2019}{\text{Traffic}2019} \times 100 \quad (1) \text{ (Adapted From [1])}$$

The data points obtained from utilising equation (1) were used to create plots in order to visualise the changes in traffic patterns. An example can be seen in [Figure 4](#).

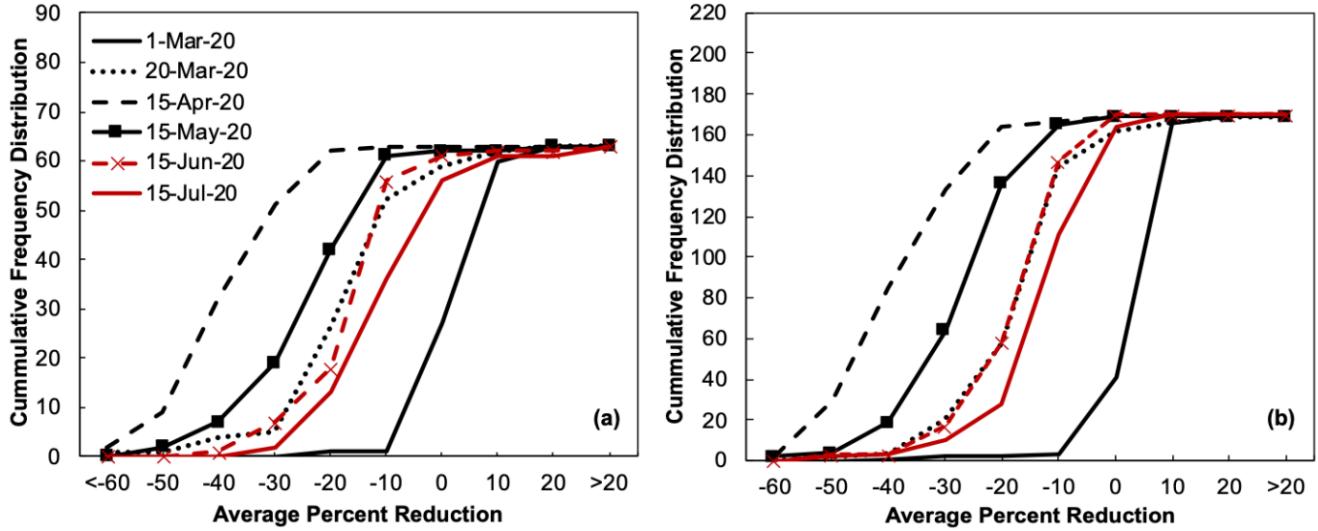


Figure 4: CFD of the percentage change in traffic volume observed in North Carolina (a) and Virginia (b) in the year 2020 [1, Fig. 2].

On the other hand, Gao and Levinson's [\[2\]](#) method focussed on analysing the changes in traffic patterns during the morning hours by exploring the reasons why vehicle traffic peaked at two times during the morning hours, otherwise known as the 'Double-Humped' phenomenon. The authors proceeded to determine the potential peaks in the diurnal curve using equation [\(2\)](#).

$$S(p_t)_l = \frac{y_{pt} - y_{pt-1}}{x_{pt} - x_{pt-1}} > 0; \quad S(p_t)_r = \frac{y_{pt+l} - y_{pt}}{x_{pt+l} - x_{pt}} < 0 \quad (2) \text{ (Adapted from [2])}$$

where:

- $S(p_t)$ = potential peak.
- $S(p_t)_l$ = left slope to the peak.
- $S(p_t)_r$ = right slope to the peak.
- y_{pt} = y-axis value.
- x_{pt} = x-axis value.

Therefore, if the value of $S(p_t)_r$ is less than 0 (right slope is negative) and the value of $S(p_t)_l$ is bigger than 0 (left slope is positive), then the data point p_t is a peak.

Once the peak values have been identified, the double-humped phenomenon can be observed. This can be illustrated by the peak points ‘ P_a ’ and ‘ P_b ’ in [Figure 5](#), where ‘ P_c ’ represents a valley.

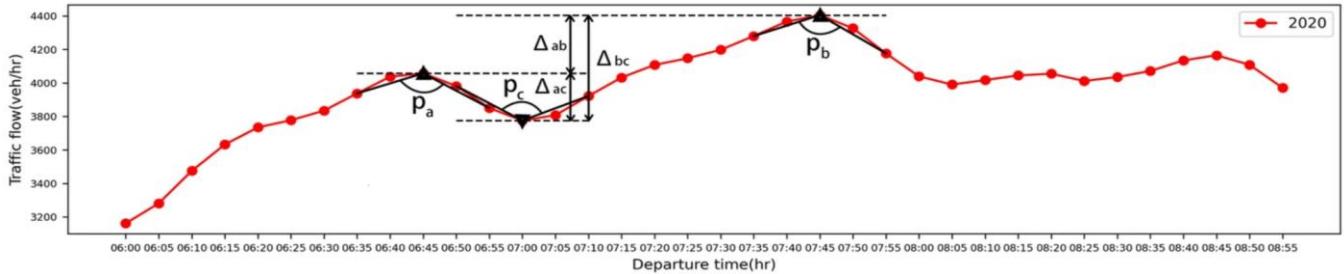


Figure 5: Diurnal curve showcasing the traffic flow rate in the city of Los Angeles in the year 2020 [2, Fig. 1].

Overall, both studies used different methodologies in order to quantify the changes in traffic patterns. Gao and Levinson have selected datasets from the years 2018, 2019, 2020, and 2021, whereas Goenaga *et al.* looked at pre-pandemic (2019) and during the pandemic (2020) datasets exclusively. Gao and Levinson focussed their research on studying the changes in traffic volume by implementing broad techniques, while Goenaga *et al.* implemented specific techniques to study the presence of a phenomenon while showcasing the different levels of traffic flow rate throughout different cities in the United States of America.

With regards to road safety and volume of road incidents, sources [\[18\]-\[28\]](#) collected their data by conducting literature review, accessing online portals, and contacting the police department to provide vehicle accident records. The analysis was conducted by producing the relevant graphs (comparison plots, ‘box and whisker’ plots, bar charts).

With regards to analysing the environmental impacts, the authors of [\[34\]](#) obtained their data regarding the levels of toxic pollutants present in the atmosphere from an air quality report produced in the year 2020 by the European Environment Agency (EEA) [\[37\]](#). Using this data, the publishers determined the average levels of nitrogen dioxide in the atmosphere before, during, and after the pandemic. Using these averages, the reduction of nitrogen dioxide levels in the atmosphere was visualised by creating and comparing graphs after the restrictive procedures have been lifted, while the procedures were implemented, and before the arrival of the pandemic. This can be seen in [Figure 3](#).

2.5. Summary

Based on the reviewed literature sources, it is evident that the COVID-19 pandemic had a noticeable impact on day-to-day life. The key findings observed are as follows:

- Noticeable reduction in vehicle traffic volume during the enforcement of restrictive measures.
- There has been a resurgence in vehicle traffic volume after the pandemic has subsided, but not as high as prior years.
- A new phenomenon emerged during the pandemic which gave an indication of which industries were impacted the most.
- The majority of countries noticed a reduction in fatalities and injuries related to vehicle incidents, however some countries reported that there has been little to no effect on road safety.
- Due to the enforcement of restrictive procedures and subsequent reduction in vehicle traffic volume during the pandemic, toxic pollutants that are present in the atmosphere have been reduced significantly.
- Different methodologies were utilised to assess the impact of the pandemic on vehicle traffic patterns, road safety, and greenhouse gas emissions.

Overall the literature indicates that the pandemic has caused a decline in vehicle traffic volume, however it would have been beneficial if Goenaga *et al.* [1] extended their research to study the trends in traffic patterns after the pandemic has subsided. Gao and Levinson [2] did in fact carry out their research to study the changes in traffic patterns in years prior to the pandemic and after it has subsided in different cities. However, their research focussed heavily on studying the presences of a phenomenon that appeared during the pandemic.

Road safety has improved drastically during the pandemic as the majority of sources agree that vehicle crashes and injuries relating to road incidents have decreased. The pandemic's impact on the environment was fully expected as once again policies set by the government resulted in the decrease in the usage of personal vehicles and public transport. Other policies also mandated that some industrial sectors had to be shut down temporarily, with employees working remotely. All of these governmental decisions resulted in the decrease of greenhouse gas emissions. However as stated before, even though the emission of toxic pollutants have decreased, 93% of toxic pollutants were still present in the atmosphere due to them having a long lifespan.

In later chapters of this report, the changes in traffic patterns will be analysed and discussed in a similar fashion to [1] and [2] by showing visual representations and illustrating descriptive statistics. The changes in traffic patterns and levels of pollutants present in the atmosphere will be analysed using hypotheses testing and regression analysis.

3. Methodology

3.1. Data Gathering

As stated before, the traffic flow rate data sets were obtained from the Urban Flows Observatory Sheffield portal (SUFO) [3]. The periods in which the data sets were obtained are from the 1st of August until the 31st of December (22-week period) in the years 2019 and 2023. The traffic flow rate, peak times, and the air quality data sets are analysed within this period. 14 data sets were collected in total, with 10 data sets representing the vehicle traffic flow rate, 2 data sets representing the Air Quality Index (AQI) of 3 different pollutants, and 2 data sets representing different climate variables (temperature, precipitation, wind-speed). With regards to the data sets representing the traffic flow rate, the sets were obtained from 5 different sensors that are located in the North, South, East, West, and Centre of the city of Sheffield. The AQI data sets were obtained from the air quality station located at Devonshire Green Park [4]. The climate data was obtained from a station located in the Centre of Sheffield [5]. [Figure 6](#) highlights the locations of the traffic flow rate sensors (purple marker), as well as the air quality station (blue marker), and the weather station (green marker). It is also worthy to note that the North and South traffic flow rate sensors measure the traffic going into Sheffield, while the East and West sensors measure traffic that is going out of Sheffield.

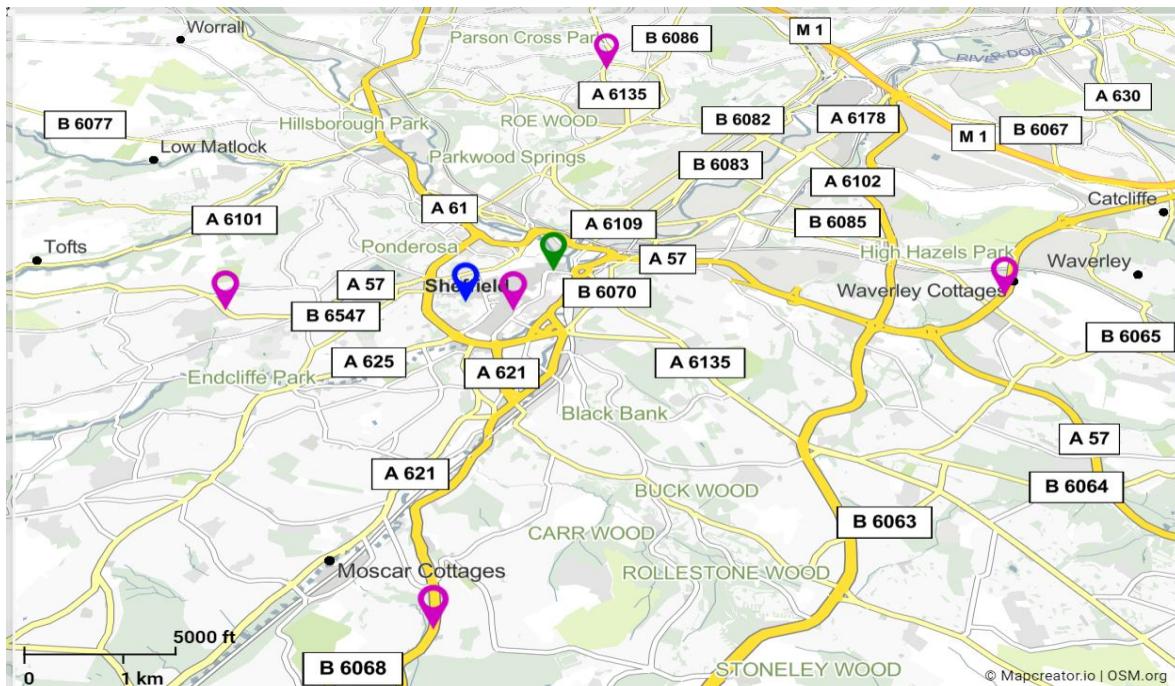


Figure 6: Locations of the traffic flow rate sensors [purple marker], air quality station [blue marker], and weather station [green marker] in the city of Sheffield. (Produced online [8]).

3.2. Comparison Plots

The main aim of this study is to observe the changes in traffic flow and the levels of toxic pollutants observed prior to the arrival of the pandemic and after the pandemic has subsided. Therefore it is appropriate to produce comparison plots to visualise these aspects. However, it can be difficult to tell if there are any differences by just visual observation. An effective method to identify if there are similarities or differences between data sets is by conducting a paired t-test.

3.3. Analysis of Traffic Flow Rate Data

A paired t-test is a hypothesis testing method which can determine how significant the similarities are between two data sets by comparing the standard deviations and the averages of the two data sets. Each paired t-test has a null hypothesis. In this case, the null hypothesis is that the two data sets are similar. After the paired t-tests have been conducted, the hypothesis is either accepted or rejected. This is represented in the tables found in the [Results](#) section using the variable ‘H’, where a value of ‘H = 0’ indicates that there is not sufficient evidence to reject the null hypothesis, and a value of ‘H = 1’ indicates that the differences between the two data sets is significant. A p-value also accompanies the value of H. The p-value represents the probability of being able to observe the differences between the two data sets, given that the null hypothesis is true. Since the confidence interval is set to 95%, a p-value less than 0.05 can indicate that the difference between the data sets that are being tested is significant. For each sensor, and for each day of the week, a paired t-test was conducted between the 2019 traffic flow rate data set and the 2023 traffic flow rate data set. For example, a paired t-test will be conducted for the Monday’s between the 1st of August and 31st of December in the years 2019 and 2023 for the Centre sensor. This will then be done for the remaining days of the week, and will then be done for the other sensors. A paired t-test should also be carried out for the AQI values of different pollutants in 2019 and 2023. Once it has been determined whether there is a difference or not between the data sets, the changes can be analysed further by observing the descriptive statistics. A descriptive statistic is a coefficient or a variable that describes the characteristics of a set of information [\[38\]](#), hence these coefficients are essential in carrying out statistical analysis. In this project the descriptive statistics that were analysed are as follows:

- Mean.
- Median.
- Variance.
- Standard deviation.
- Maximum values.

3.4. Analysis of Peak Times

Similarly to the traffic flow rate data, it is also important to compare the differences between the peak times observed in the years 2019 and 2023. The peak times are the times in a day where the vehicle flow rate is at its maximum. In this project, the peak times observed in each year were split into two data sets, the morning period and the afternoon period. The morning period and the afternoon period peak times were visualised using ‘box and whisker’ plots. The ‘box and whisker’ plots show the spread of the data, as well as highlight the median, the mean, the outliers, and the maximum and minimum values. Once again the descriptive statistics of the peak times were analysed in order to provide more details about the changes between the data sets.

3.5. Regression Analysis

Building regression models can also help in analysing the changes of pollutants present in the atmosphere. Climate variables such as wind-speed, temperature, and precipitation could result in an increase or decrease in the concentration of certain pollutants such as NO₂, PM₁₀, and PM_{2.5} [39]-[40]. Since these pollutants are also emitted from the exhaust pipe of all petrol powered vehicles, a model can be built in order to predict the concentration of a certain pollutant present in the atmosphere using the following as input variables:

- Levels of precipitation.
- Wind-speed.
- Temperature.
- Vehicle Flow Rate.

After the models have been built, the effects of the traffic flow rate can then be isolated, and it can be determined whether the traffic flow rate has contributed to the concentration levels of these pollutants.

4. Results

4.1. Changes in Traffic Patterns

[Figures 7-11](#) illustrate the average traffic flow rate in the years 2019 and 2023 in the city of Sheffield from the 1st of August (Week 1) until the 31st of December (Week 22).

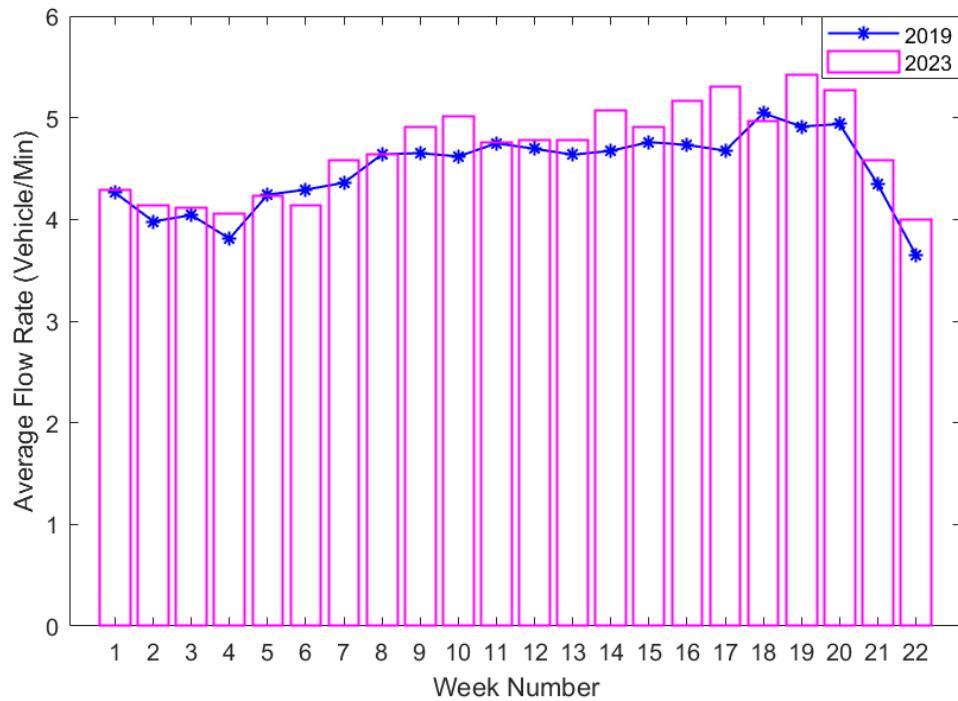


Figure 7: Average traffic flow rate in the Centre of Sheffield between the 1st of August and 31st of December in the years 2019 and 2023.

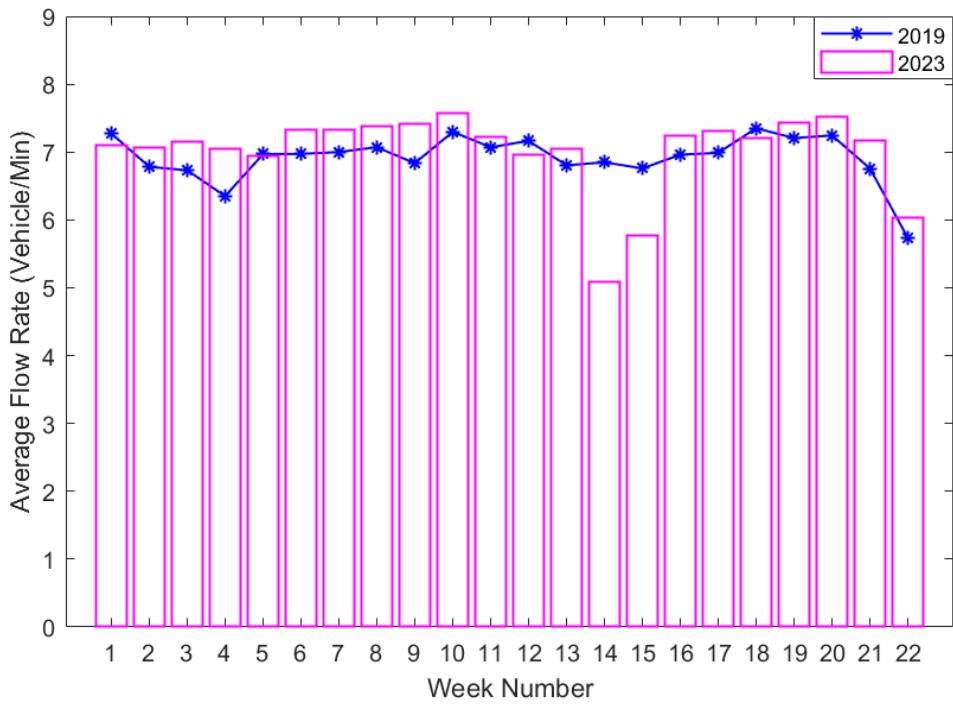


Figure 8: Average traffic flow rate in the North of Sheffield between the 1st of August and 31st of December in the years 2019 and 2023.

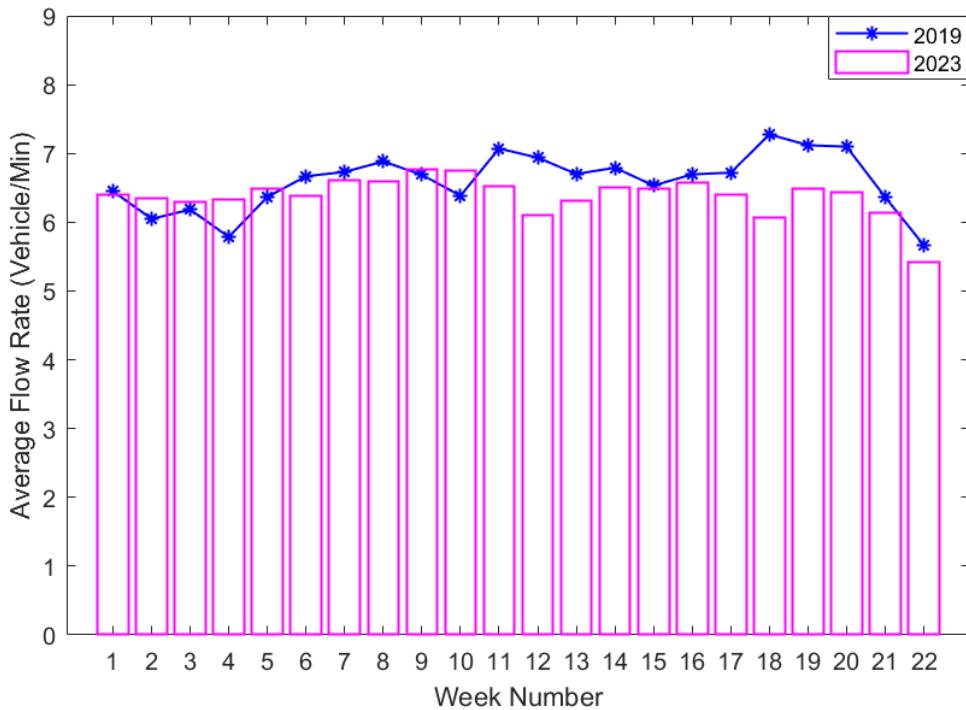


Figure 9: Average traffic flow rate in the South of Sheffield between the 1st of August and 31st of December in the years 2019 and 2023.

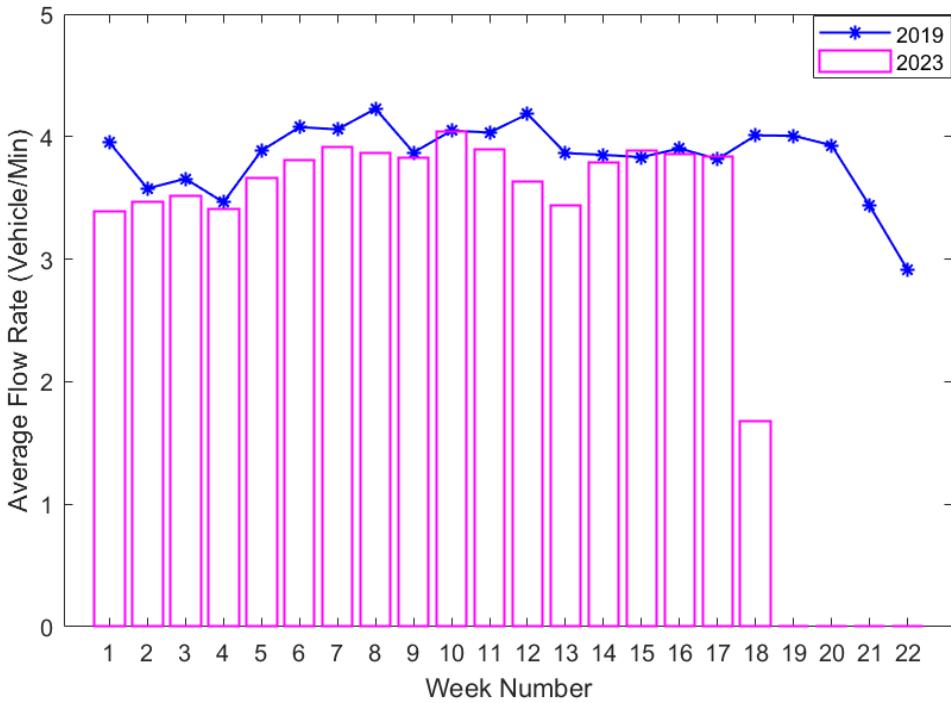


Figure 10: Average traffic flow rate in the West of Sheffield between the 1st of August and 31st of December in the years 2019 and 2023.

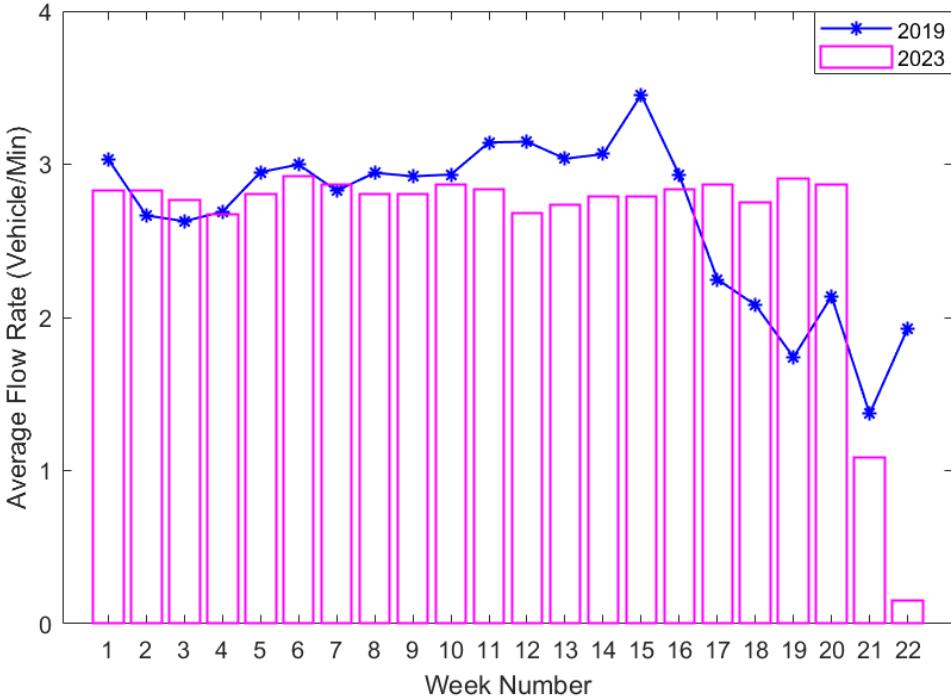


Figure 11: Average traffic flow rate in the East of Sheffield between the dates 1st of August and 31st of December in the years 2019 and 2023.

By visual inspection, the North and South (inbound traffic) sensors recorded the highest rate of traffic flow, while the East and West (outbound traffic) recorded the lowest rates of traffic flow. This indicates that the inbound traffic is greater than the outbound traffic in both years. By Observing [Figures 7-11](#), it is very difficult to notice the changes in traffic flow rate as the average traffic flow rate observed across the 22 week period is very similar in the Centre, North, and South regions. The changes in traffic flow rate are more noticeable in the East and West regions, as there are weeks where the average traffic flow rate observed in 2019 is either significantly higher or significantly lower than the average traffic flow rate observed in 2023. In order to determine whether there has been significant changes in the data sets, a hypothesis test is required. The results of the hypothesis tests are discussed in section [4.1.1](#).

4.1.1. Paired t-tests

[Table 3](#) presents the outcomes following the execution of the paired t-tests on the traffic flow rate data as detailed in [section 3.3](#), which encompasses observations from the period spanning 1st of August until the 31st of December (22 week period) in the years 2019 and 2023 in the city of Sheffield.

Table 3: The results of the paired t-tests conducted between the traffic flow rate data sets in 2019 and 2023 in the city of Sheffield for each day of the week for 5 different sensors.

	Centre Sensor		North Sensor		South Sensor		East Sensor		West Sensor	
	H	p-value	H	p-value	H	p-value	H	p-value	H	p-value
Monday	0	0.126	1	1.98e-05	1	1.15e-05	0	0.0698	1	9.92e-33
Tuesday	1	0.0154	1	0.024	1	0.0063	1	0.0057	1	4.14e-15
Wednesday	1	6.23e-08	1	1.51e-04	0	0.5752	1	9.13e-05	1	3.95e-07
Thursday	1	1.09e-07	1	1.14e-06	1	0.0295	1	8.90e-04	1	1.63e-36
Friday	1	0.0422	1	5.34e-23	1	6.46e-15	1	3.16e-20	1	5.04e-85
Saturday	1	3.86e-79	1	1.05e-42	1	4.48e-07	1	9.40e-16	1	2.01e-72
Sunday	1	0.004	0	0.1009	1	0.0251	1	3.90e-18	1	4.36e-49

It is safe to conclude that the majority of the data sets are different since a value of ‘H = 1’ accompanied with a p-value less than 0.05 has been returned after conducting the paired t-test for the majority of the data sets. The tests highlighted in orange in [Table 3](#) indicate that there isn’t sufficient evidence to suggest that there is a significant difference between the data sets. To prove that these data sets are similar, they can be visualised in the form of ‘box and whisker’ plots. This is seen in [Figure 12](#).

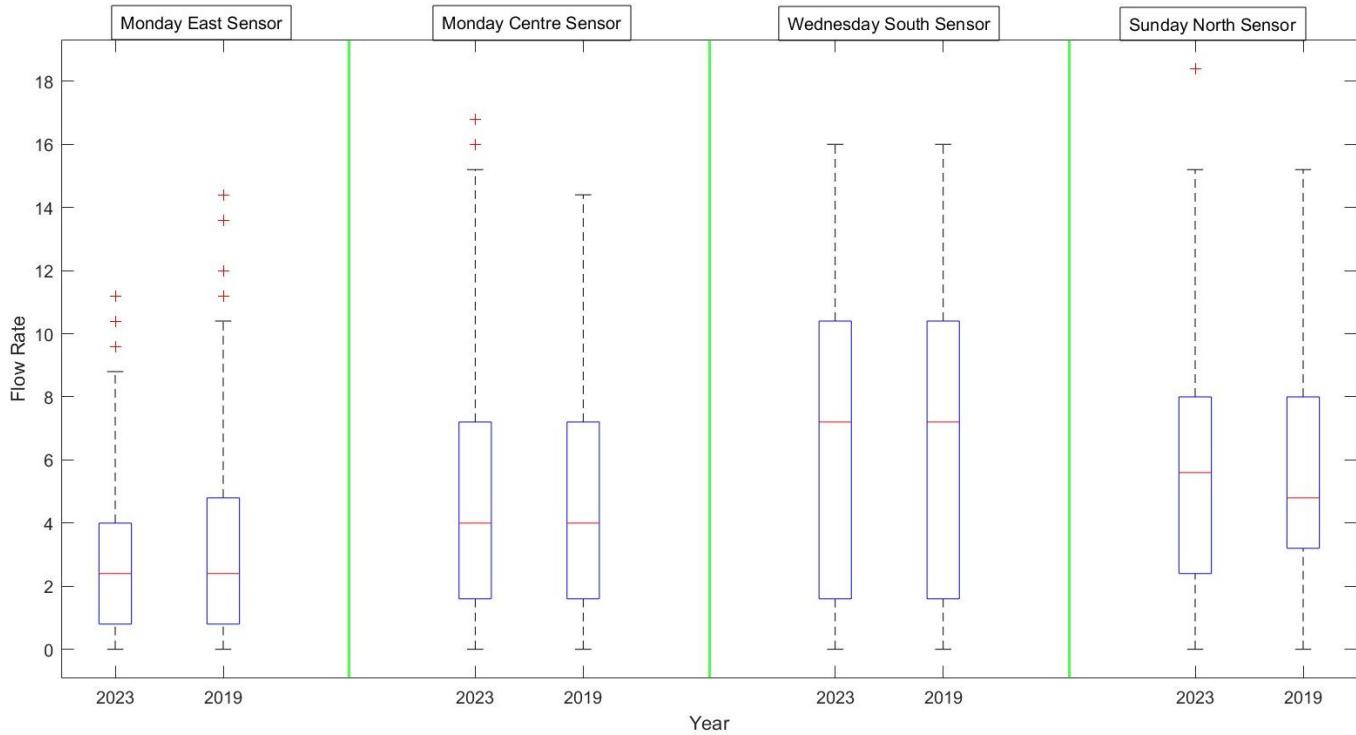


Figure 12: The similarities between the data sets that did not reject the null hypothesis after conducting the paired t-test for the traffic flow rate data as described in section 3.3.

Since the majority of the results of the paired t-tests indicate that there is a difference between the data sets, it can be concluded that the vehicle traffic patterns have indeed changed. To further analyse these changes, the descriptive statistics of the traffic flow rate data should be analysed.

4.1.2. Descriptive Statistics

Tables 4–5 show the results of computing the descriptive statistics for the vehicle flow rate in the years 2019 and 2023. Table 6 shows the percentage change between the descriptive statistics observed in both years.

Table 4: Descriptive statistics for the vehicle traffic flow rate (vehicle/minute) data in the year 2019 in the city of Sheffield.

	<u>Centre</u>	<u>West</u>	<u>South</u>	<u>North</u>	<u>East</u>
Mean	4.49	3.85	6.60	6.92	2.68
Median	4.00	4.00	7.20	7.20	2.40
Variance	8.93	9.18	19.93	18.69	5.59
Standard Deviation	2.99	3.03	4.46	4.32	2.36
Maximum	20.80	27.2	17.60	27.20	17.60

Table 5: Descriptive statistics for the vehicle traffic flow rate (vehicle/minute) data in the year 2023 in the city of Sheffield.

	<u>Centre</u>	<u>West</u>	<u>South</u>	<u>North</u>	<u>East</u>
Mean	4.69	2.95	6.38	7.01	2.61
Median	4.80	1.60	6.40	8.00	2.40
Variance	11.08	9.21	18.15	19.02	4.94
Standard Deviation	3.33	3.03	4.26	4.36	2.22
Maximum	18.40	20.00	20.80	33.60	14.40

[Table 6](#) shows the percentage change between the data observed in Tables [5](#) and [4](#). Cells coloured in shades of green indicate an increase, whereas shades of red indicate a decrease. Cells coloured in grey indicate no changes.

Table 6: Percentage change in the descriptive statistics for the vehicle traffic flow rate (vehicle/min) between the years 2023 and 2019.

	<u>Centre</u>	<u>West</u>	<u>South</u>	<u>North</u>	<u>East</u>
Mean	+4.5%	-23.4%	-3.3%	+1.3%	-2.6%
Median	+20%	-60%	-11.1%	+11.1%	0%
Variance	+24.1%	+0.3%	-8.9%	+1.8%	-11.6%
Standard Deviation	+11.4%	0%	-4.5%	+0.9%	-5.9%
Maximum	-11.5%	-26.5%	+18.2%	+23.5%	-18.2%

According to [Table 6](#), the Centre and North regions of Sheffield have witnessed an increase in vehicle flow rate, whereas the South, East, and West of Sheffield have generally witnessed a reduction in traffic flow rate. The variance of the traffic flow rate has increased significantly by 24.1% in the Centre of Sheffield, whereas the South and East regions have witnessed a reduction in the variance by 8.9% and 11.6% respectively. It is interesting to note that the standard deviation for the West region hasn't changed, indicating that the spread of the traffic flow rate data remained the same relative to the mean. Even though the spread of the data points hasn't changed, the volume of traffic has decreased significantly in the West of Sheffield since the mean and the median were reduced by 23.4% and 60% respectively. Although there has been changes in traffic flow rate, overall the changes are considered to be minor

across all regions except the West, which can suggest that the restrictions set during the pandemic did not have long term impacts on the traffic flow rate observed in Sheffield.

4.2. Shifts in Peak Times

In this section, the shifts in the peak times were analysed as described in [section 3.4](#) by presenting ‘box and whisker’ plots which showcase the distribution of the peak times throughout different regions in the city of Sheffield in the years 2019 and 2023, as well as presenting and discussing the descriptive statistics of the peak times during the morning and afternoon periods. It is crucial to observe the shifts in the peak times in order to determine the pandemic’s long-lasting impacts on commuting times.

[Figures 13-20](#) illustrate the distribution of the peak times during the morning and afternoon hours in the years 2019 and 2023 in the form of ‘box and whisker’ plots. The plots contain the following visuals:

- Horizontal line: represents the median; ‘+’ symbol: represents the mean.
- ● and ▲: represent the peak time data points from the 2019 and 2023 data sets respectively.
- The p-value: represents the significance level between the 2019 and 2023 data sets after conducting a paired t-test.

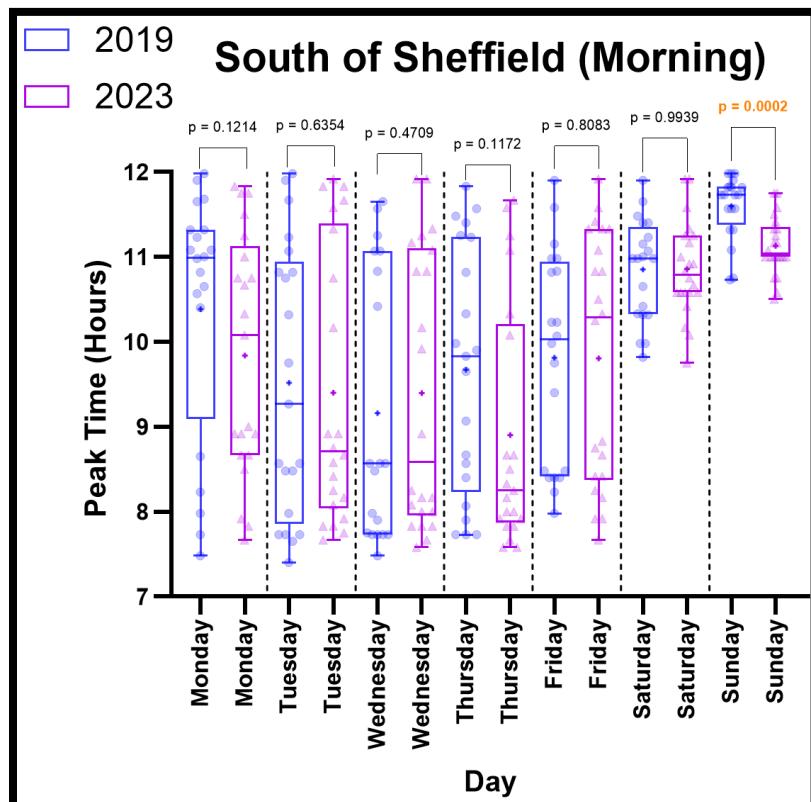


Figure 13: Distribution of the peak times during the morning hours in the South of Sheffield in the years 2019 and 2023.

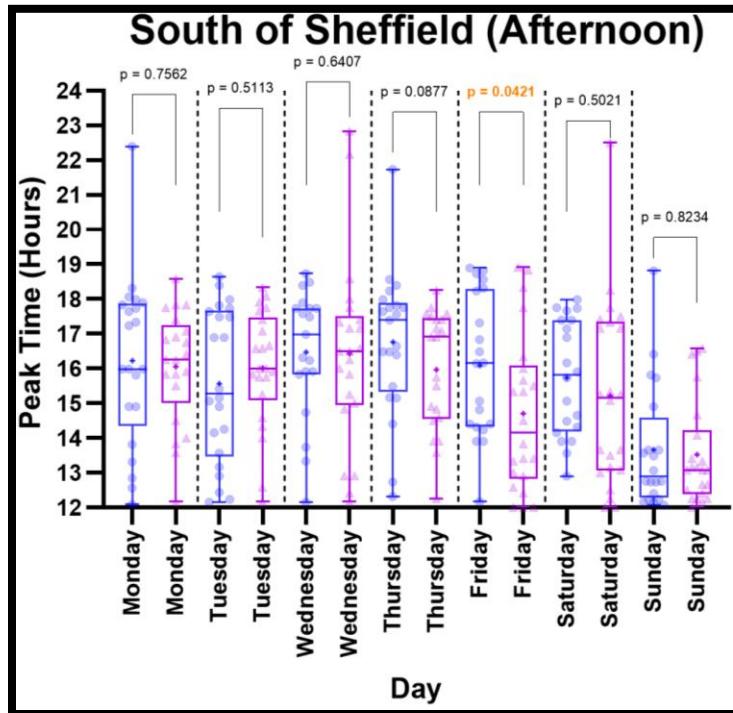


Figure 14: Distribution of the peak times during the afternoon hours in the South of Sheffield in the years 2019 and 2023.

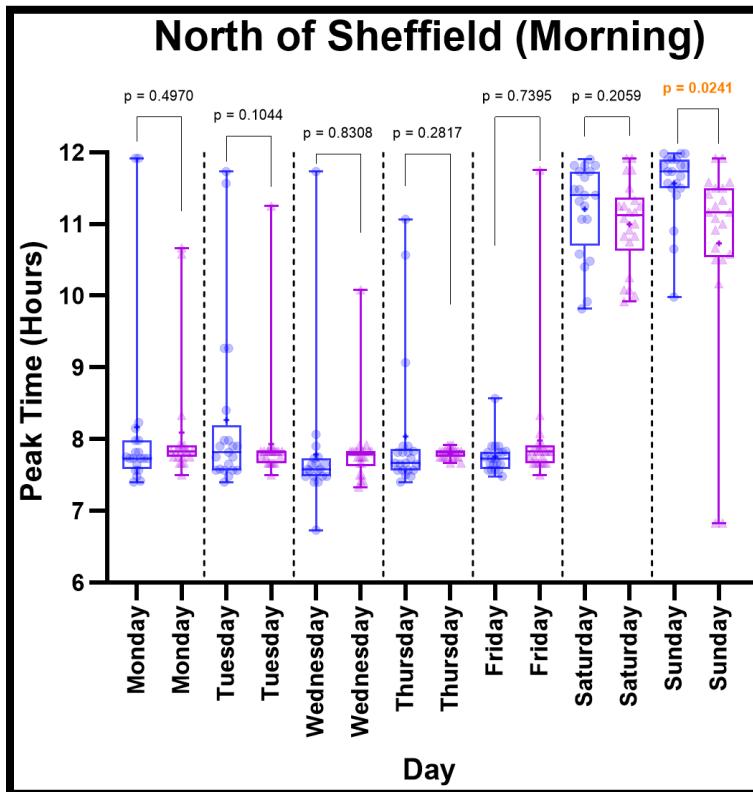


Figure 15: Distribution of the peak times during the morning hours in the North of Sheffield in the years 2019 and 2023.

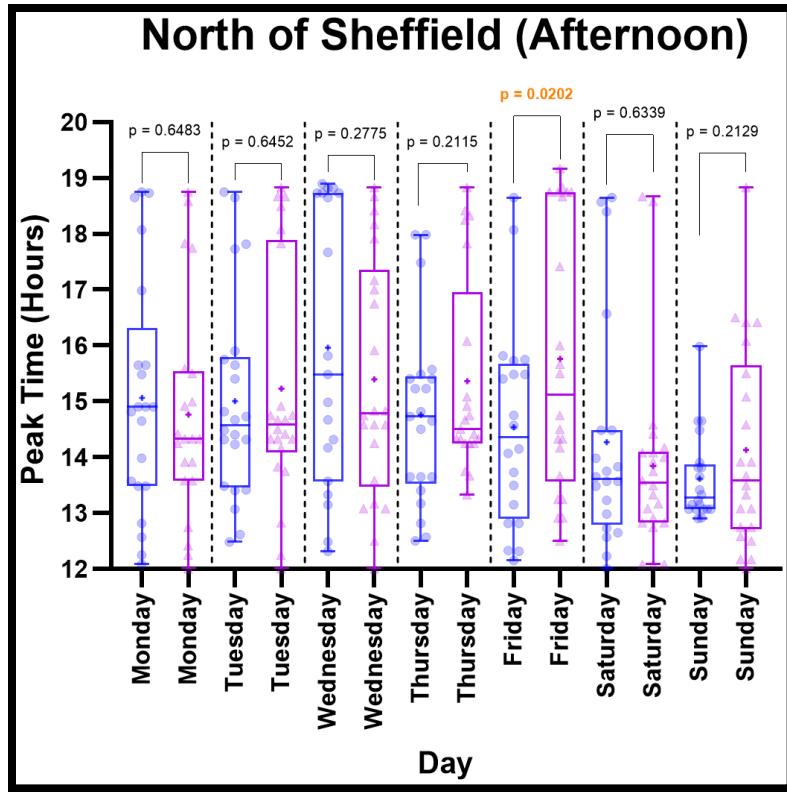


Figure 16: Distribution of the peak times during the afternoon hours in the North of Sheffield in the years 2019 and 2023.

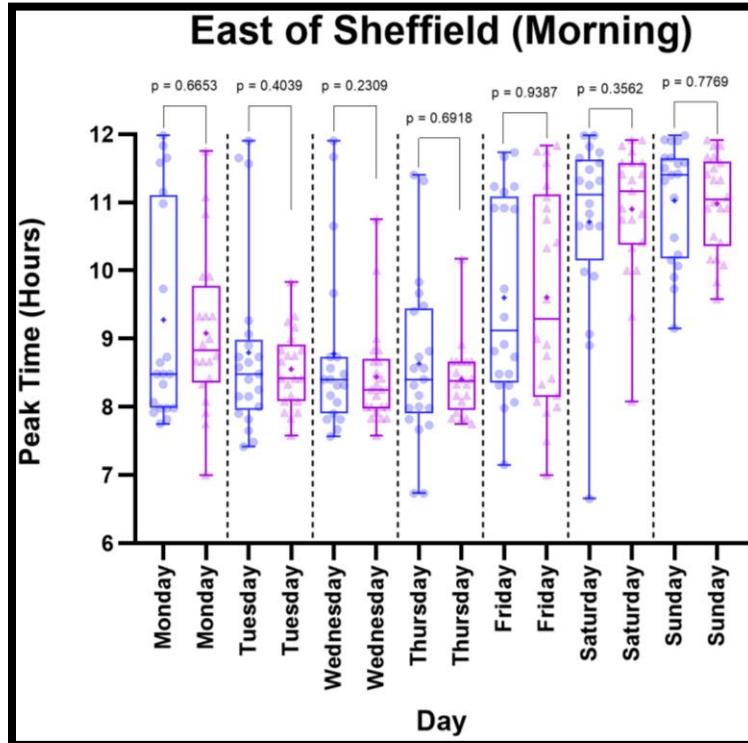


Figure 17: Distribution of the peak times during the morning hours in the East of Sheffield in the years 2019 and 2023.

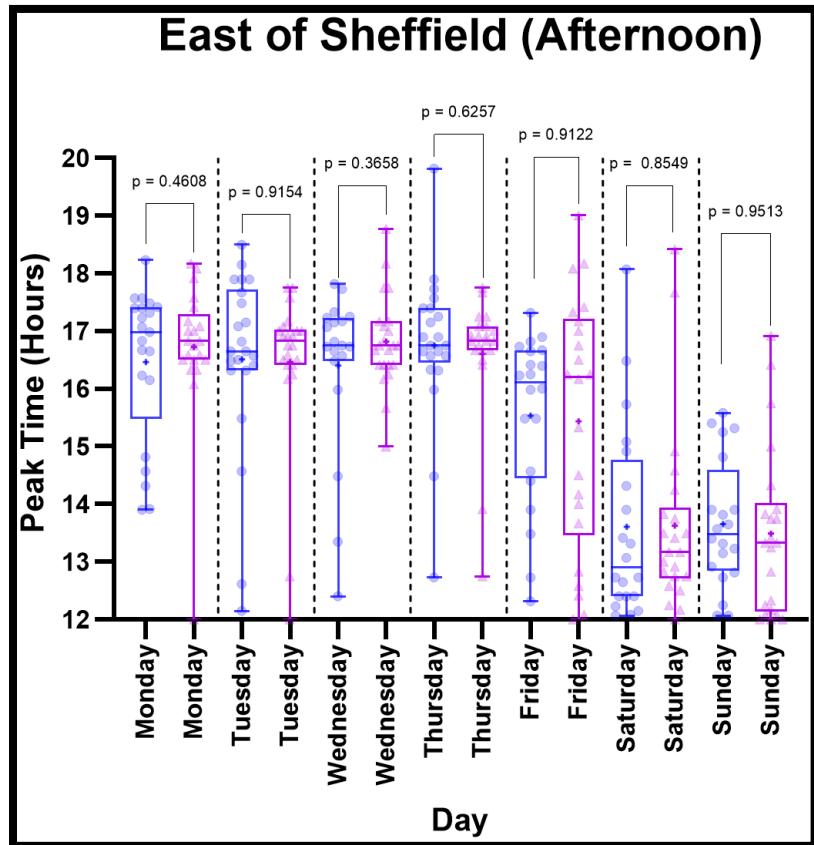


Figure 18: Distribution of the peak times during the afternoon hours in the East of Sheffield in the years 2019 and 2023.

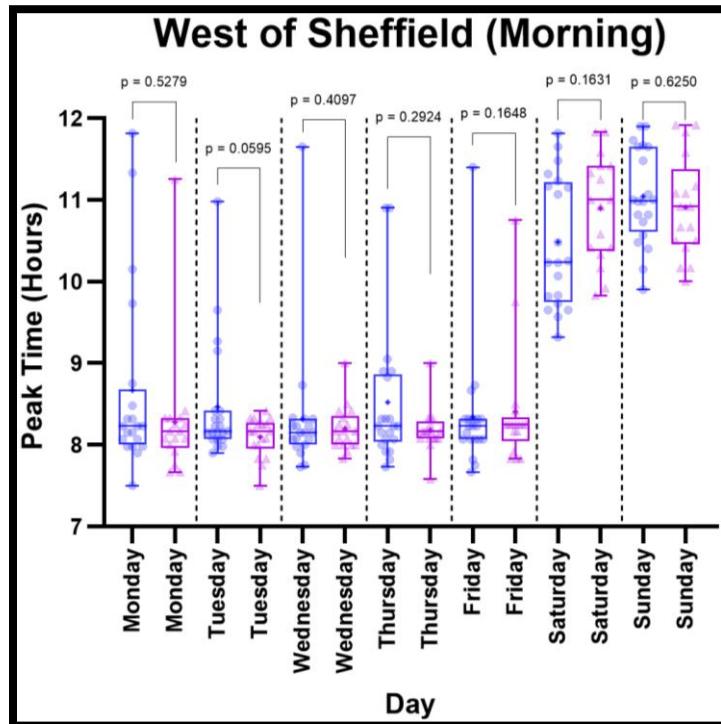


Figure 19: Distribution of the peak times during the morning hours in the West of Sheffield in the years 2019 and 2023.

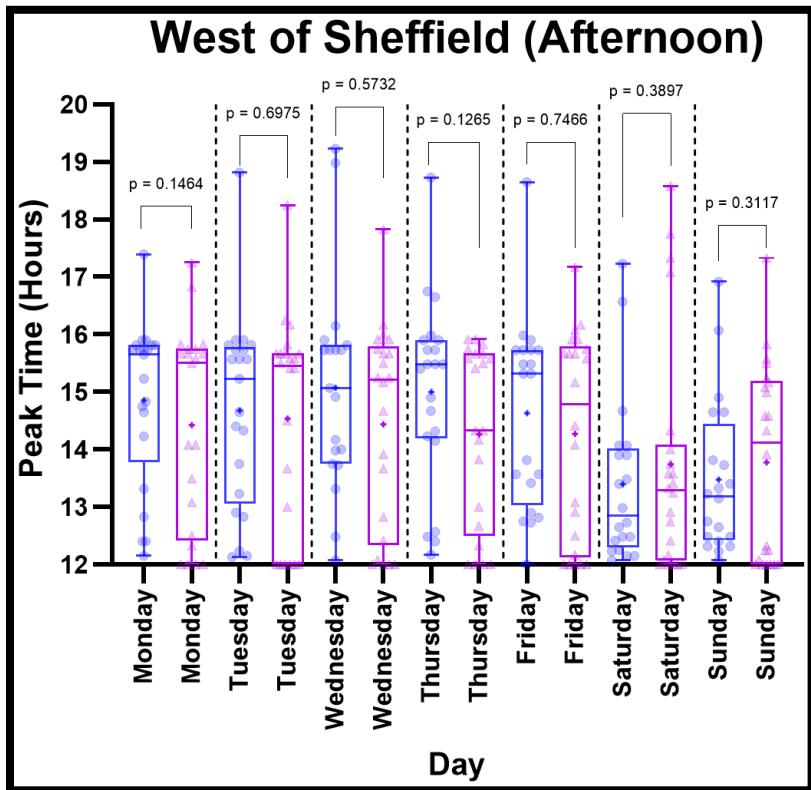


Figure 20: Distribution of the peak times during the afternoon hours in the West of Sheffield in the years 2019 and 2023.

By visual inspection of [Figures 13-20](#), the peak times have generally shifted backwards in the year 2023 when compared to the year 2019. Commuting in the morning generally takes place between 8 and 11 AM, whereas commuting in the afternoon generally takes place between 2 and 5 PM. The confidence level was set to 95% before conducting the paired t-tests. Therefore for a given pair of data sets, if the p-value is less than 0.05, the difference between the data sets is said to be significant. The p-values highlighted in orange in [Figures 13-16](#) indicate a significant difference between the data sets. Since the majority of the hypothesis tests that were conducted between the data sets visualised in [Figures 13-20](#) had a p-value greater than 0.05, it can be concluded that there has been minor shifts in the peak times as the data sets are similar. However, similarly to the traffic flow rate data, it is better to analyse the descriptive statistics to observe the changes in the peak times in more detail.

4.2.1. Descriptive Statistics

[Tables 7-14](#) found in [Appendix 3](#) show the percentage change between the descriptive statistics of the peak times in both the morning and afternoon periods observed in the years 2019 and 2023 for each region in the city of Sheffield. Tables [15](#) and [16](#) show the average percentage change between the descriptive statistics for the morning and afternoon peak times observed in the years 2019 and 2023 across all regions. Similarly to [Table 6](#), the colouring of the cells in tables [15](#) and [16](#) indicate the intensity of the increase/decrease of the descriptive statistics' values. Shades of green indicate an increase, shades of red indicate a decrease, and the colour grey indicates no changes.

Table 15: Average percentage change in descriptive statistics during the morning period.

	<u>North</u>	<u>South</u>	<u>East</u>	<u>West</u>
Mean	-3.8%	-2.3%	-3.9%	-21.7%
Median	0%	-5%	-0.3%	-1.0%
Variance	+570.8%	-0.4%	+57.5%	+2464.3%
Standard Deviation	+93.5%	-0.6%	+20.3%	+381.4%
Maximum	-2.9%	-0.4%	-5.7%	-10.5%

Table 16: Average percentage change in descriptive statistics during the afternoon period.

	<u>North</u>	<u>South</u>	<u>East</u>	<u>West</u>
Mean	+1.3%	-2.3%	+0.2%	-1.8%
Median	-0.4%	-2.0%	+0.3%	0%
Variance	+71.1%	+17.5%	+7.5%	+26.9%
Standard Deviation	+21.9%	+3.1%	-0.3%	+11%
Maximum	+3.6%	+0.1%	+1.5%	-5.2%

As evident from [Table 15](#), on average, the peak times in the morning period have shifted backwards in 2023 when compared to the peak times in 2019. The commuting times varied significantly in 2023 relative to the mean, and this is due to the massive percentage change increase in the variance and the standard deviation. According to [Table 16](#), on average, the peak times remained the same in the afternoon period, albeit there has been very small changes. Similarly to the morning period, the peak times varied significantly relative to their means in the afternoon. The maximum peak time in the afternoon period has increased, which indicates that there has been some instances where people are commuting at a later time during the afternoon period in the year 2023. The minor shifts observed in both the morning and the afternoon periods indicate that the pandemic did not have long-lasting effects on commuting times. This means that the majority of the population has returned to normal commuting times and resumed their

daily routines, further implying the short-lived impacts of the pandemic on mobility and social interactions.

4.3. Changes in the Levels of Pollutants

As mentioned in [section 2.3](#) of the report, modes of transportation including personal vehicles are responsible for the emission of toxic pollutants like nitrogen dioxide (NO_2) and particulate matter (PM_{10} and $\text{PM}_{2.5}$). It is important to observe the changes in the levels of these pollutants in the atmosphere in order to establish whether the air quality has improved or worsened. The Air Quality Index (AQI) provides a numerical value which represents the level of pollution in the atmosphere. The higher the AQI, the greater the level of pollution [41]. [Table 17](#) shows the different ranges of AQI values and their impact on human health.

Table 17: AQI values and their corresponding levels of concern. Reproduced from [41].

AQI Values	Level of Concern
0 - 50	Good
51 – 100	Moderate
101 – 150	Unhealthy for sensitive groups
151 – 200	Unhealthy
201 – 300	Very unhealthy
301 - 500	Hazardous

[Figure 21](#) shows the comparison between the AQI values of different pollutants in the years 2019 and 2023 between the 1st of August and 31st of December in the city of Sheffield.

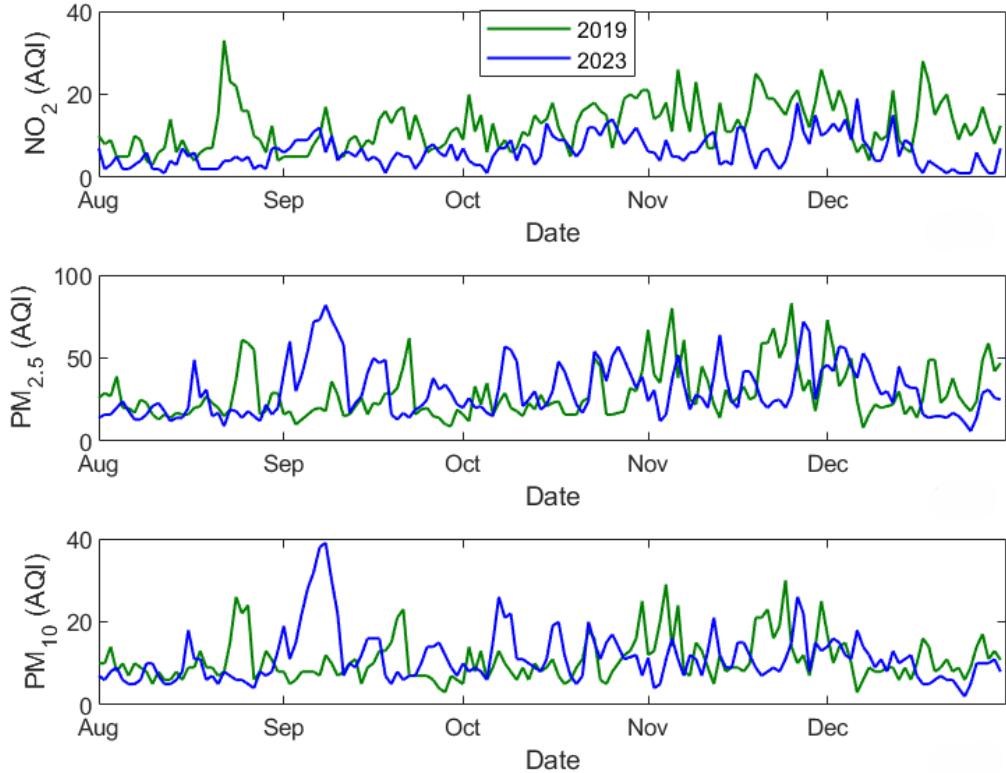


Figure 21: AQI values of NO_2 , $PM_{2.5}$, and PM_{10} in the years 2019 and 2023 in the city of Sheffield.

As depicted from [Figure 21](#), the levels of nitrogen dioxide were much higher in 2019 when compared to 2023, whereas the levels of $PM_{2.5}$ and PM_{10} were similar for both years. Alternatively, paired t-tests could be executed in order to conclude whether there has been changes or not.

4.3.1. Paired t-tests

Similarly to the traffic flow rate data, a paired t-test can be executed in order to determine if there is a significant difference between the levels of pollutants observed in the years 2019 and 2023. [Table 18](#) shows the results of the paired t-tests. The data sets were categorised based on the day of the week, similarly to [Table 3](#).

Table 18: Results of paired t-tests that have been ran on pollutant data recorded from the Devonshire Green air quality station in the city of Sheffield in the years 2019 and 2023.

	NO ₂ data sets		PM ₁₀ data sets		PM _{2.5} data sets	
	H	p-value	H	p-value	H	p-value
Monday	1	0.0002	0	0.9137	0	0.5800
Tuesday	1	0.0005	0	0.8787	0	0.6470
Wednesday	1	0.0003	0	0.8540	0	0.7692
Thursday	1	0.0005	0	0.6028	0	0.9300
Friday	1	0.0002	0	0.3822	0	0.5031
Saturday	1	0.0003	0	0.9319	0	0.4293
Sunday	1	0.0014	0	0.7224	0	0.7236

Due to the high p-values (p-value > 0.05) , there is insufficient evidence to reject the null hypothesis the results highlighted in orange in [Table 18](#) indicate that the PM_{2.5} and PM₁₀ data sets are similar, whereas there is a significant difference in the nitrogen dioxide data sets across the days of the week since the p-value is less than 0.05 for each day of the week. This indicates that the nitrogen dioxide levels for each day between August 1st and December 31st in 2023 were significantly different from the levels observed during the same period in 2019. This is also reflected in [Table 19](#) which shows the mean AQI values for the pollutants in both years and the corresponding percentage change.

Table 19: Average AQI values for pollutants in the years 2019 and 2023, and the corresponding percentage change.

Pollutant	Mean AQI (2019)	Mean AQI (2023)	Percentage Change
NO ₂	12	6	-50%
PM _{2.5}	29	31	+6.9%
PM ₁₀	11	11	0%

It is evident from [Table 19](#) that the levels of NO₂ have decreased significantly, and there was little to no change in the levels of PM₁₀ and PM_{2.5}.

4.3.2. Regression Analysis

As described in [section 3.5](#), a model was built in order to predict the AQI values of a certain pollutant across the period spanning 1st of August to 31st of December using the traffic flow rate, temperature, wind-speed, and precipitation data as the input variables in the year 2019. The 2019 model will then be fed with the input data from the year 2023. The predicted and actual AQI values in the year 2023 can then be compared and a conclusion can be established whether the levels of pollutants have changed or not.

[Figure 22](#) shows the performance of the models that are used to predict the AQI values of NO₂, PM₁₀, and PM_{2.5} in the year 2019.

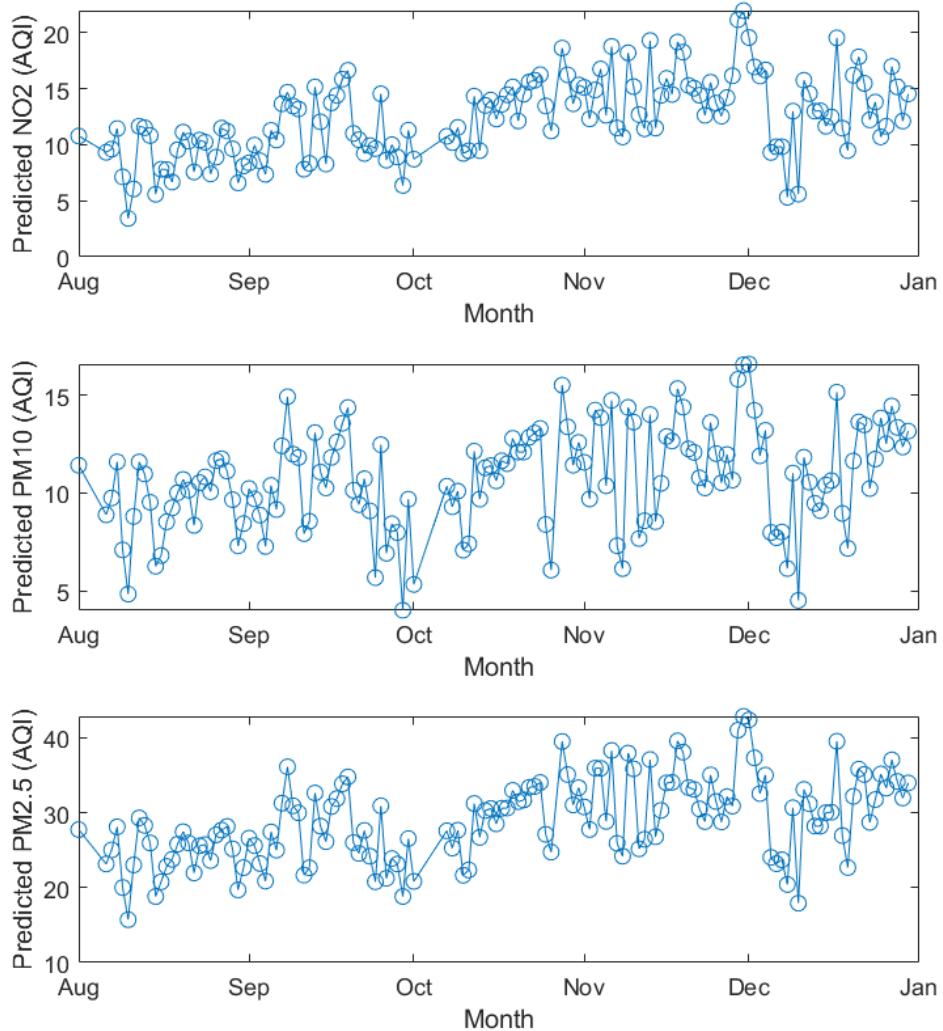


Figure 22: Performance of the models used for predicting the AQI values of NO₂, PM₁₀, and PM_{2.5} in the year 2019.

[Figure 23](#) compares the AQI values of NO₂, PM₁₀, and PM_{2.5} in the year 2023 with the predicted AQI values that were obtained using the models that were trained on the data set from the year 2019, and then fed with the input data from the year 2023.

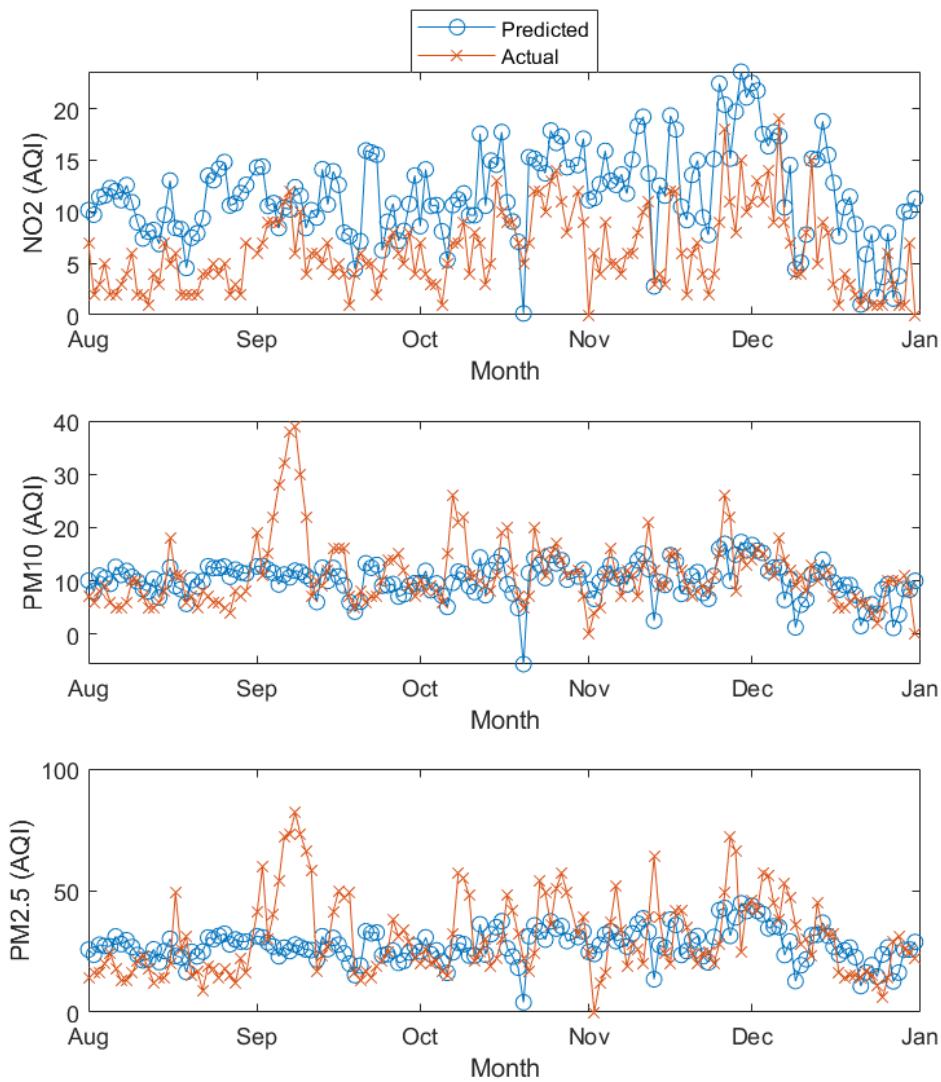


Figure 23: Comparison between the actual and predicted AQI values of NO_2 , PM_{10} , and $\text{PM}_{2.5}$ in the year 2023, and then fed with the input data from the year 2023.

By visually observing [Figure 23](#), it is evident that the models trained using the data from the year 2019 have overestimated the AQI values of NO_2 , and underestimated the AQI values of PM_{10} and $\text{PM}_{2.5}$. This is seen more clearly in [Figure 24](#), where the figure depicts the difference between the actual and the predicted values.

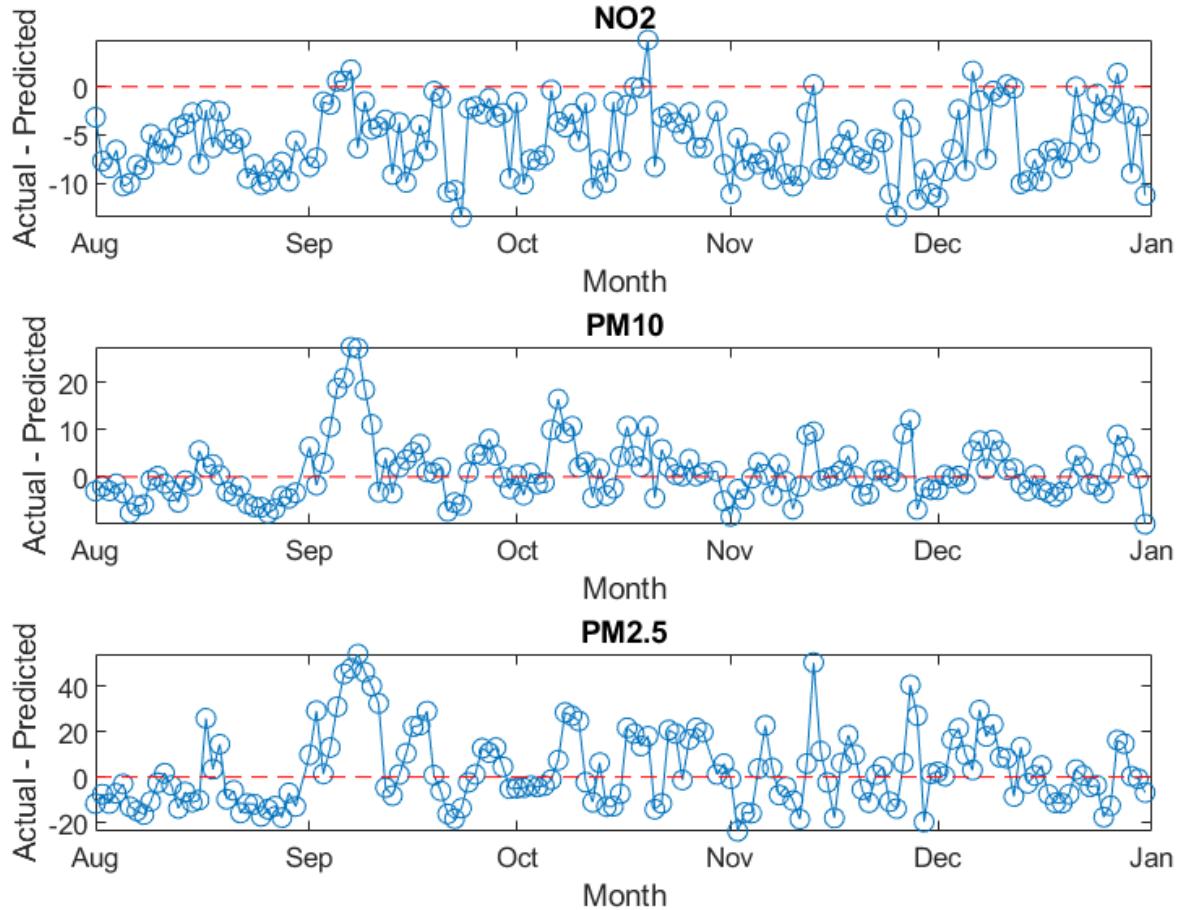


Figure 24: The difference between the actual and predicted AQI values of NO₂, PM₁₀, and PM_{2.5} in the year 2023.

The majority of the data points in the NO₂ plot in [Figure 24](#) are below the zero line, indicating that the model has overestimated the AQI values of NO₂. The data points in the PM₁₀ and PM_{2.5} plots are mainly above the zero line, indicating that the respective models have underestimated the AQI values of PM₁₀ and PM_{2.5}. [Figure 24](#) shows the difference between the actual and predicted values, however it does factor in the traffic flow rate as one of the input variables. In order to determine whether the traffic flow rate has contributed to the increase/decrease in the AQI values, another set of models can be trained without the use of the traffic flow rate data, and the difference between the actual and predicted data can be compared with the data in [Figure 24](#). This is seen in [Figure 25](#).

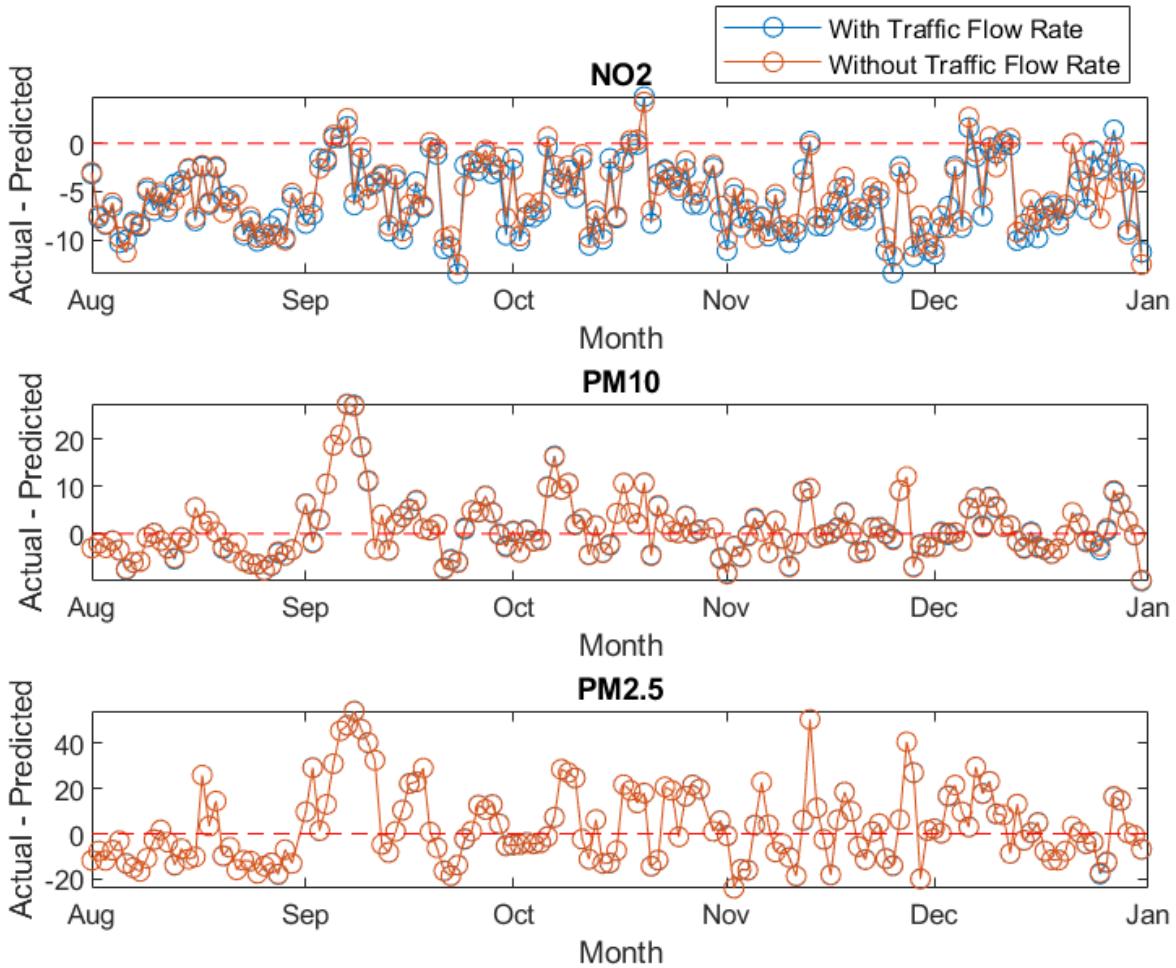


Figure 25: Comparing models in their ability at predicting the levels of pollutants where a group of models integrate the traffic flow rate as one of the input variables, and the others do not.

Observing [Figure 25](#) leads to the conclusion that vehicle traffic flow rate had little to no impact on the presence of NO₂, PM_{2.5}, and PM₁₀ in the atmosphere since the data points in both scenarios are overlapping. The Centre sensor was used as the source of the traffic flow data used in building the models, and according to [Table 6](#), the mean and the median of the traffic flow rate has increased by 4.5% and 20% respectively in the Centre of Sheffield in the year 2023 when compared to the traffic flow rate data in 2019. If there was a positive relationship between the traffic flow rate and the AQI values of the pollutants, the difference between the actual and predicted data sets in the year 2023 after removing the traffic flow rate as an input variable would be lower than the difference when the traffic flow rate is integrated as one of the input variables. Since there is no change between the models, one can assume that the traffic flow rate did not contribute to the increase/decrease in the AQI values of these pollutants.

In order to provide evidence that there is no relationship between the pollutants and the traffic flow rate, a simple model can be built where the levels of a certain pollutant are predicted using the traffic flow rate as the only input variable. Since pollutants tend to saturate when plotted against the source of pollution (which is assumed to be traffic flow in this case), a 3rd order polynomial can be used instead of a linear one in order to assess the relationship. These models are represented in [Figures 26-28](#).

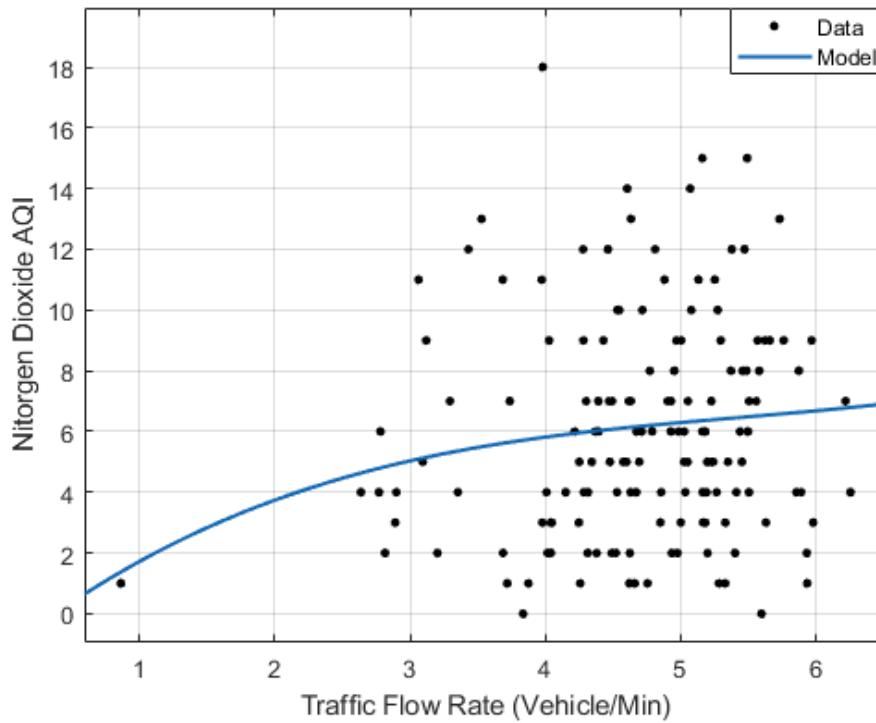


Figure 26: Predicting NO₂ levels given the traffic flow rate levels.

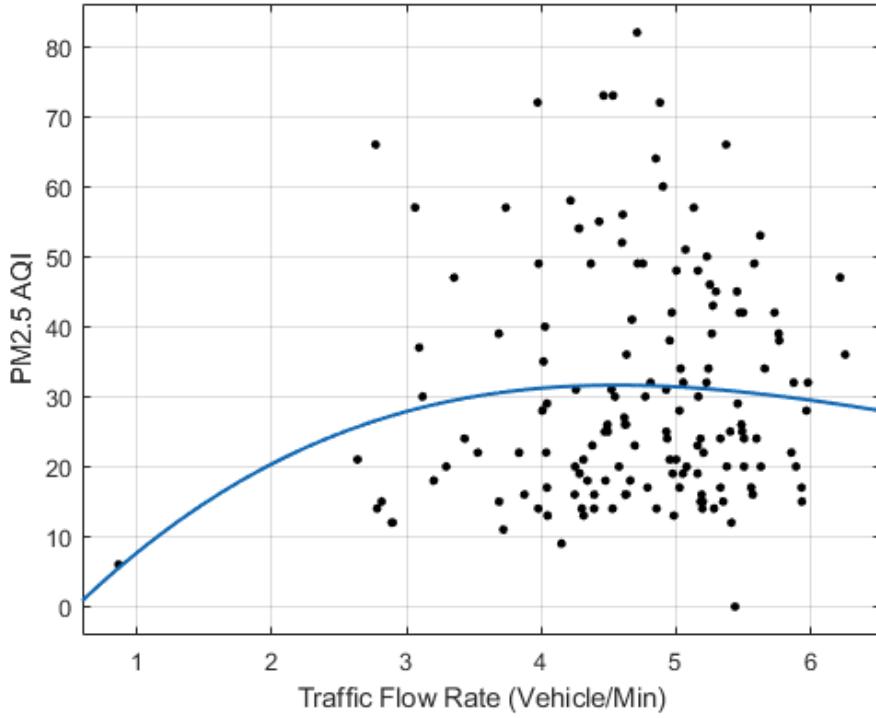


Figure 27: Predicting PM_{2.5} levels given the traffic flow rate levels.

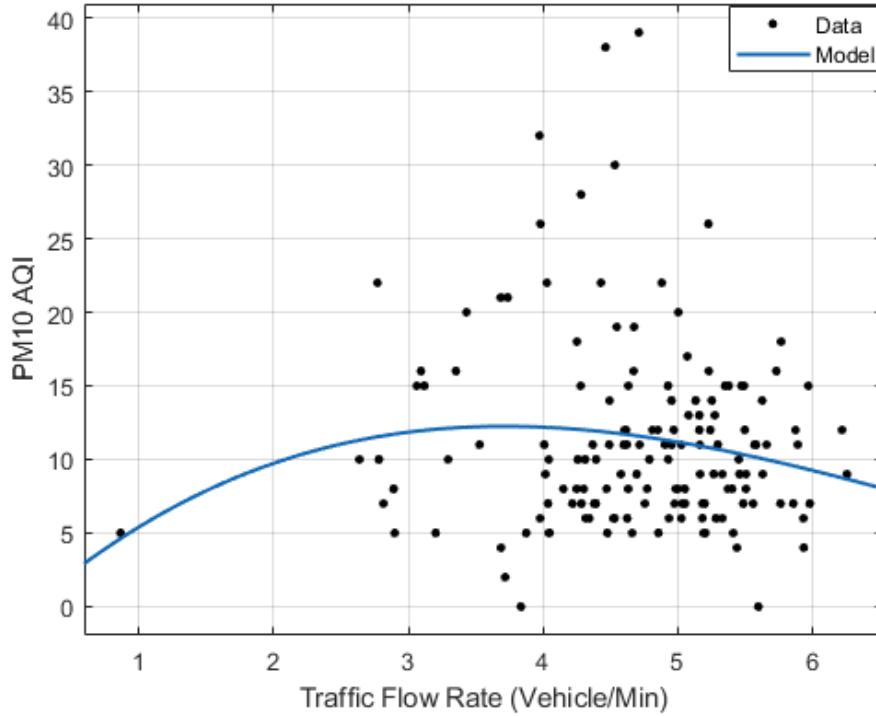


Figure 28: Predicting PM₁₀ levels given the traffic flow rate levels.

[Table 20](#) shows the performance metrics for the models in [Figures 26-28](#).

Table 20: Performance metrics of the models in figure 19-21.

Model	SSE	R²	RMSE
Figure 26	2.09e+03	2.31e-02	3.7664
Figure 27	3.94e+04	2.06e-02	16.3629
Figure 28	6.03e+03	2.37e-02	6.404

The high ‘Sum of Squares due to Error’ (SSE) values indicate that the models are very inaccurate, and the low R² values indicate that the models are unable to capture the variance in the data points. Therefore, there isn’t enough evidence to suggest that there is a relationship between each of the pollutants and the traffic flow rate since the models in [Figures 26-28](#) have very poor performance metrics.

5. Discussions & Conclusions

In this research, different statistical analysis approaches were applied in order to determine how the traffic volume and the levels of pollutants have changed when comparing data from the year 2023 to the data in 2019. The changes in the peak times have also been analysed, as well as the impact of the rate of traffic and the climate on the levels of pollutants present in the atmosphere. Therefore, the aims of this project which were discussed in [section 1.1](#) of the report have been achieved.

The results of the hypothesis testing indicate that there is a difference between the traffic flow rate data sets observed in both years, as well as a noticeable difference in the levels of nitrogen dioxide observed in both years. The inbound traffic into Sheffield has increased by 1.3% in the North with an increase in the maximum flow rate by 23.5%, whereas in the South the inbound traffic has decreased by 3.3%. The outbound traffic in the West decreased by 23.4%, whereas the outbound traffic in the East decreased by 2.6%. The Centre of Sheffield has witnessed an increase in traffic flow rate by 4.5%, with a 24.1% increase in the variation of traffic flow. The outbound morning peak times in the West shifted backwards by 21.7%, with a significant increase in the variation of the peak times by 2464.3%. Similarly, the peak times observed in the morning hours in the North, South, and the East have all shifted backwards by 3.8%, 2.3%, and 3.9% respectively. In the afternoon, the North and East of Sheffield witnessed a very minor forward shift in the peak times by 1.3% and 0.2% respectively. Whereas the South and West witnessed a backwards shift by 2.3% and 1.8% respectively.

The levels of 10 micrometres particulate matter (PM_{10}) have remained the same, whereas the levels of 2.5 micrometres particulate matter ($PM_{2.5}$) increased by 6.9%. It is also interesting to note that the levels of nitrogen dioxide decreased by 50%. Based on the models produced using the 2019 data in [section 4.3.2](#), it can be concluded that the models had overestimated the levels of NO_2 and underestimated the levels of PM_{10} and $PM_{2.5}$ in the year 2023. When the effects of traffic flow rate have been isolated from the models, the prediction of the models did not change when compared to the models that did not isolate the effects of traffic flow rate.

These results indicate that after the pandemic had subsided, the traffic flow rate observed in the West of Sheffield suffered a significant decrease in traffic volume. The Centre and North regions have witnessed an increase in traffic flow rate as well as an increase in the variation of the traffic flow rates. On the other hand, the East of Sheffield has suffered a loss in variation of traffic flow rates by 11.6%, as well as a decrease in the maximum recorded flow rates by 18.2%.

The peak times in the morning period have shifted backwards on average, with the West of Sheffield witnessing the most significant shift. However, there was a significant increase in the variation and spread of the peak time data points in the North, South, and West regions during the morning hours. The afternoon period peak times have experienced a very minor shift, with the North and East shifting forwards, and the South and West shifting backwards. The most significant changes can once again be found in the variance where the North and West had an increase by 71.1% and 26.9% respectively. The remaining regions have experienced very minor changes during the afternoon period, implying that there has been no impact on commutation during those hours. Tables [6](#) and [15](#) indicate that the West of Sheffield was impacted the most in terms of changes in traffic flow rate and peak times. This means that the residents in the West region chose to commute less and at earlier times in the year 2023. This implies that the policies that were set in place during the pandemic era had long-lasting effects on the West of Sheffield, whereas the other regions witnessed minor/moderate changes to the traffic flow rate and peak times, thus implying that the policies set previously had short-term effects on those regions.

With regards to the AQI values of the different pollutants, there has been little to no change in the values of PM_{2.5} and PM₁₀. However, the AQI values of NO₂ decreased by half the value witnessed in 2019. Indicating that air quality has improved. However, these recordings were taken in the Centre of Sheffield at Devonshire Green air quality station, where in the same region the mean traffic flow rate has increased by 4.5%, and the median has increased by 20%. Due to the regression models showing no difference when isolating and incorporating the effects of traffic flow rate, it can be said that the traffic flow rate in the Centre of Sheffield had no direct impact on the concentrations of these pollutants. Since the models built using the 2019 data have overestimated the levels of NO₂, and underestimated the levels of PM₁₀ and PM_{2.5}, it can be concluded that the levels of NO₂ were greater in 2019, and the levels of PM₁₀ and PM_{2.5} in 2019 were less than or equal to the levels observed in 2023. This is supported by the results found in Tables [18](#) and [19](#).

In conclusion, the COVID-19 pandemic had subtle impact on traffic flow rate, peak times, and the concentration of pollutants in the city of Sheffield. Although there has been minor/intermediate changes in traffic volume and peak times, the significant decrease in nitrogen dioxide was particularly notable. However, the levels of PM_{2.5} and PM₁₀ experienced little to no changes despite there being some changes in the levels of traffic. The pandemic's impact on traffic flow rate did not emerge as a significant contributing factor to the variations observed in pollutant levels. This indicates that other factors, such as

changes in transportation modes and industrial activity might have played a more significant role in shaping the status of the air quality in the city of Sheffield in the year 2023.

This key points from this investigation can be summarised as follows:

- Increase in traffic flow rate in the Centre and North regions, and a decrease in traffic flow rate in the West, South, and East regions after the pandemic had subsided.
- Increase in variation of traffic flow rates in the Centre and the North, and a decrease in variation of traffic flow rates in the West and East regions after the pandemic had subsided. No changes in the variation in the West region.
- Minor backward shifts in the peak times during the morning hours across the North, South, and East regions after the pandemic had departed. Significant backwards shift observed in the West region during the morning hours.
- Significant increase in peak time variability during the morning hours across the North, East, and West of Sheffield after the pandemic had departed.
- Very minor shifts in the peak times during the afternoon hours across all regions after the pandemic had departed.
- Increase in variability of peak times across all regions during the afternoon hours after the pandemic had subsided.
- Significant decrease in the concentration of nitrogen dioxide , and little to no changes in the concentrations of 10 and 2.5 micrometres particulate matter recorded in the Centre region of Sheffield after the pandemic had subsided.
- No correlation between the rate of traffic flow and the concentrations of NO₂ ,PM₁₀, and PM_{2.5} recorded in the Centre region of Sheffield.
- Overall the pandemic had minor effects on the traffic flow rate, pollutant level, and commuting times after it had subsided.

5.1. Limitations

The data obtained from the Urban Flows Observatory portal [3] was not consistent as there were plenty of occasions where there were plenty of data values missing for different dates, or the sensor corresponding to a certain region would go off-line for an unknown reason which would result in a loss of data. The missing values were adhered to by following a certain data cleaning method, however the loss of real data could have impacted the final results. The scope of the data could have also impacted the final conclusion.

A period of 22 weeks was looked at in the years 2019 and 2023 since a year-long worth of data was not possible to obtain due to the UFO portal [3] being offline from January to June in 2019.

It would be expected that as the traffic flow rate increases, the AQI values of certain pollutants should also increase. However, this did not happen in this project. This leads to another limitation which is the location of the Centre traffic flow rate sensor relative to the locations of the air quality station and the weather station which can be seen in [Figure 29](#). The data reported by these stations could be independent of the traffic flow rate data as the distances between the stations and the sensor is relatively large. Therefore, this discrepancy could explain the poor 3rd order models produced in section [4.3.2](#), and can then explain why a relationship between the traffic flow rate and the AQI values of the pollutants could not be established.

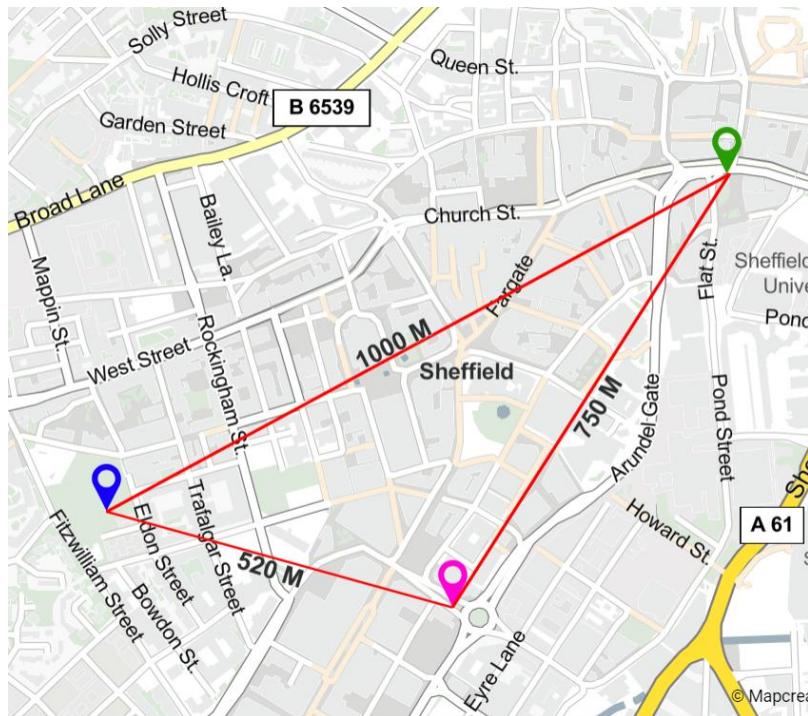


Figure 29: Distances between the Centre traffic flow rate sensor [pink marker], the air quality station [blue marker], and the weather station [green marker] (Produced online [8]).

Future research on this topic can therefore look at a larger scope of data, ensure source of data is reliable and not faulty, implement data cleaning methods to ensure that there are no outliers or missing data, ensure sensors collecting data are within a relatively small proximity in order to establish a relationship between the measured variables, and therefore be able to build a strong predictive model.

6. References

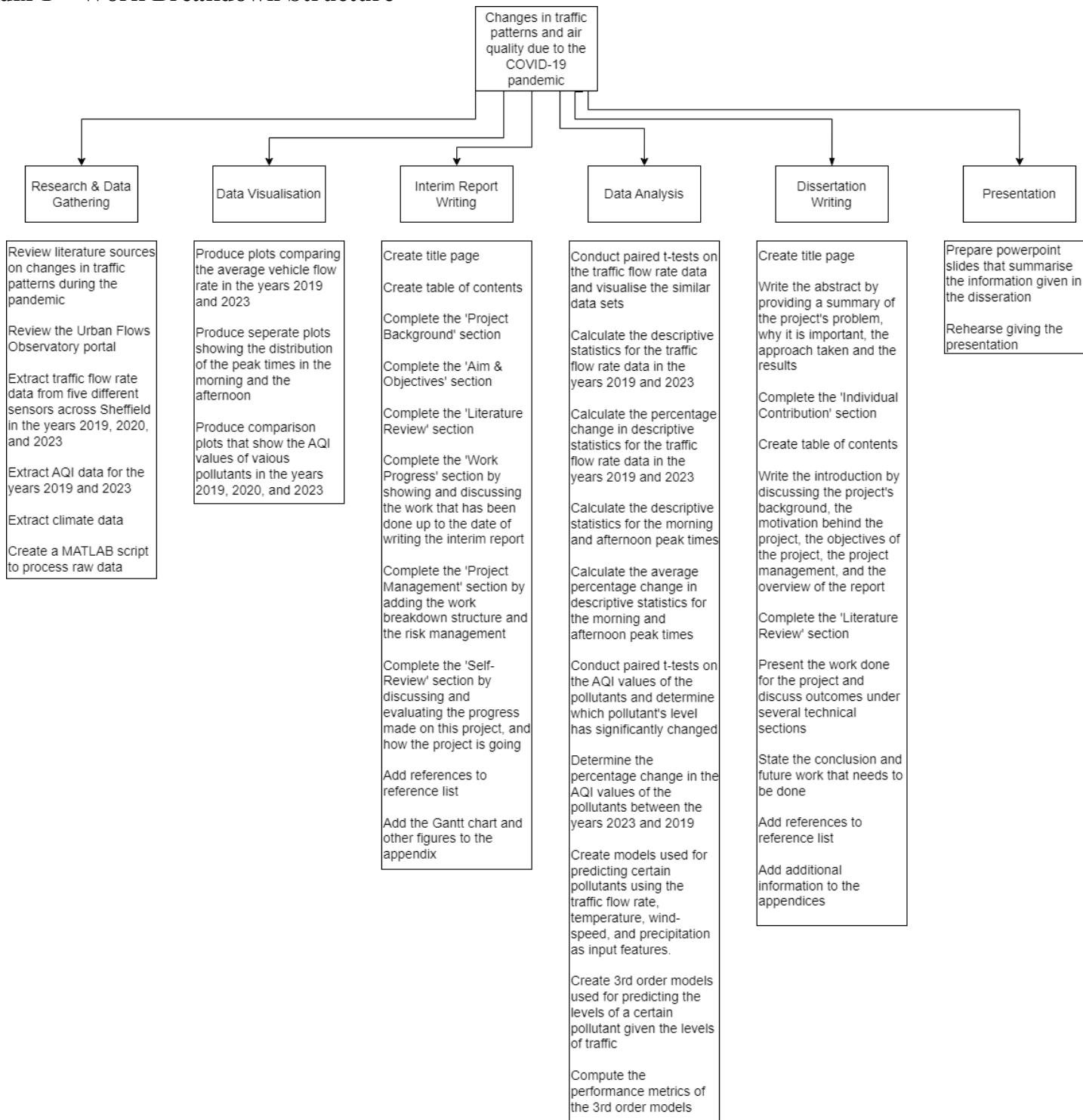
- [1] B. Goenaga, N. Matini, D. Karanam, and B. S. Underwood, “Disruption and recovery: Initial assessment of COVID-19 traffic impacts in North Carolina and Virginia”, *J. Transp. Eng., Part A: Syst.*, vol. 147, no. 4, p. 06021001, Apr. 2021. [Online]. Available: <https://doi.org/10.1061/jtepb.0000518>
- [2] Y. Gao and D. Levinson, “A bifurcation of the peak: New patterns of traffic peaking during the COVID-19 era”, *Transportation*, Sep. 2022. [Online]. Available: <https://doi.org/10.1007/s11116-022-10329-1>
- [3] “The urban flows observatory sheffield.” Urban Flows Observatory. <https://sheffield-portal.urbanflows.ac.uk/uflobin/theObservatory> (Accessed: Feb 29, 2024).
- [4] “Sheffield devonshire green air pollution: Real-time air quality index (AQI).” aqicn.org. <https://aqicn.org/city/united-kingdom/chesterfield-loundsley-green/> (Accessed: Feb 29, 2024).
- [5] “Historical weather data for sheffield | Visual Crossing.” Weather Data & Weather API | Visual Crossing. <https://www.visualcrossing.com/weather-history/sheffield/metric/2023-08-01/2023-12-31> (Accessed: Mar 10, 2024).
- [6] MathWorks. *MATLAB*. (2023).
- [7] Dotmatics. *GraphPad Prism 10*. (2018).
- [8] “Monday.com | A new way of working.” monday.com. <https://monday.com> (Accessed: Apr 3, 2024).
- [9] Microsoft. *Word*. (2021).
- [10] “Census and population | sheffield city council.” Homepage | Sheffield City Council. <https://www.sheffield.gov.uk/your-city-council/population-in-sheffield> (Accessed: Apr 3, 2024).
- [11] A. Haleem, M. Javaid, and R. Vaishya, “Effects of COVID-19 pandemic in daily life”, *Current Medicine Res. Pract.*, vol. 10, no. 2, pp. 78–79, March. 2020. [Online]. Available: <https://doi.org/10.1016/j.cmrp.2020.03.011>
- [12] C. L. Svihus, “Online teaching in higher education during the COVID-19 pandemic”, *Educ. Inf. Technol.*, June. 2023. [Online]. Available: <https://doi.org/10.1007/s10639-023-11971-7>
- [13] F. F. Kautsar, M. Siallagan, and Y. Palumian, “Customer decisions to use online food delivery services during the COVID-19 pandemic”, *J. Bus. Manage. Rev.*, vol. 4, no. 1, pp. 017–035, Jan. 2023. [Online]. Available: <https://doi.org/10.47153/jbmr41.5702023>

- [14] D. Bongaerts, F. Mazzola, and W. Wagner, “Closed for business: The mortality impact of business closures during the Covid-19 pandemic”, *Plos One*, vol. 16, no. 5, May. 2021. [Online]. Available: <https://doi.org/10.1371/journal.pone.0251373>
- [15] T. Galanti, G. Guidetti, E. Mazzei, S. Zappalà, and F. Toscano, “Work from home during the COVID-19 outbreak”, *J. Occupational & Environmental Medicine*, vol. 63, no. 7, Apr. 2021. [Online]. Available: <https://doi.org/10.1097/jom.0000000000002236>
- [16] A. Velias, S. Georganas, and S. Vandoros, “COVID-19: Early evening curfews and mobility”, *Social Sci. & Medicine*, vol. 292, p. 114538, Jan. 2022. [Online]. Available: <https://doi.org/10.1016/j.socscimed.2021.114538>
- [17] “Statistics on remote workers that will surprise you - apollo technical LLC.” Apollo Technical LLC. <https://www.apollotechnical.com/statistics-on-remote-workers/> (Accessed: Jan 4, 2024)
- [18] Y. Yao, T. G. Geara, and W. Shi, “Impact of COVID-19 on city-scale transportation and safety: An early experience from Detroit”, *Smart Health*, vol. 22, p. 100218, Nov. 2021. [Online]. Available: <https://doi.org/10.1016/j.smhl.2021.100218>
- [19] Ò. Saladié, E. Bustamante, and A. Gutiérrez, “COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain”, *Transp. Res. Interdisciplinary Perspectives*, vol. 8, p. 100218, Nov. 2020. [Online]. Available: <https://doi.org/10.1016/j.trip.2020.100218>
- [20] E. Michelaraki, M. Sekadakis, C. Katrakazas, A. Ziakopoulos, and G. Yannis, "A four-country comparative overview of the impact of COVID-19 on traffic safety behavior", *In 10th International Congress on Transportation Research, Future Mobility and Resilient Transport: Transition to Innovation.* p. 1-3, 2021. [Online]. Available: <https://www.nrsq.ntua.gr/geyannis/wp-content/uploads/geyannis-pc417.pdf>
- [21] B. Sedain and P. R. Pant, “Road traffic injuries in Nepal during COVID-19 lockdown”, *F1000Research*, vol. 9, p. 1209, Feb. 2021. [Online]. Available: <https://doi.org/10.12688/f1000research.26281.3>
- [22] M. Gupta, N. M. Pawar, and N. R. Velaga, “Impact of lockdown and change in mobility patterns on road fatalities during COVID-19 pandemic”, *Transp. Lett.*, vol. 13, no. 5-6, pp. 447–460, Mar. 2021. [Online]. Available: <https://doi.org/10.1080/19427867.2021.1892937>
- [23] M. Ebrahim Shaik and S. Ahmed, “An overview of the impact of COVID-19 on road traffic safety and travel behavior”, *Transp. Eng.*, vol. 9, p. 100119, Sep. 2022. [Online]. Available: <https://doi.org/10.1016/j.treng.2022.100119>

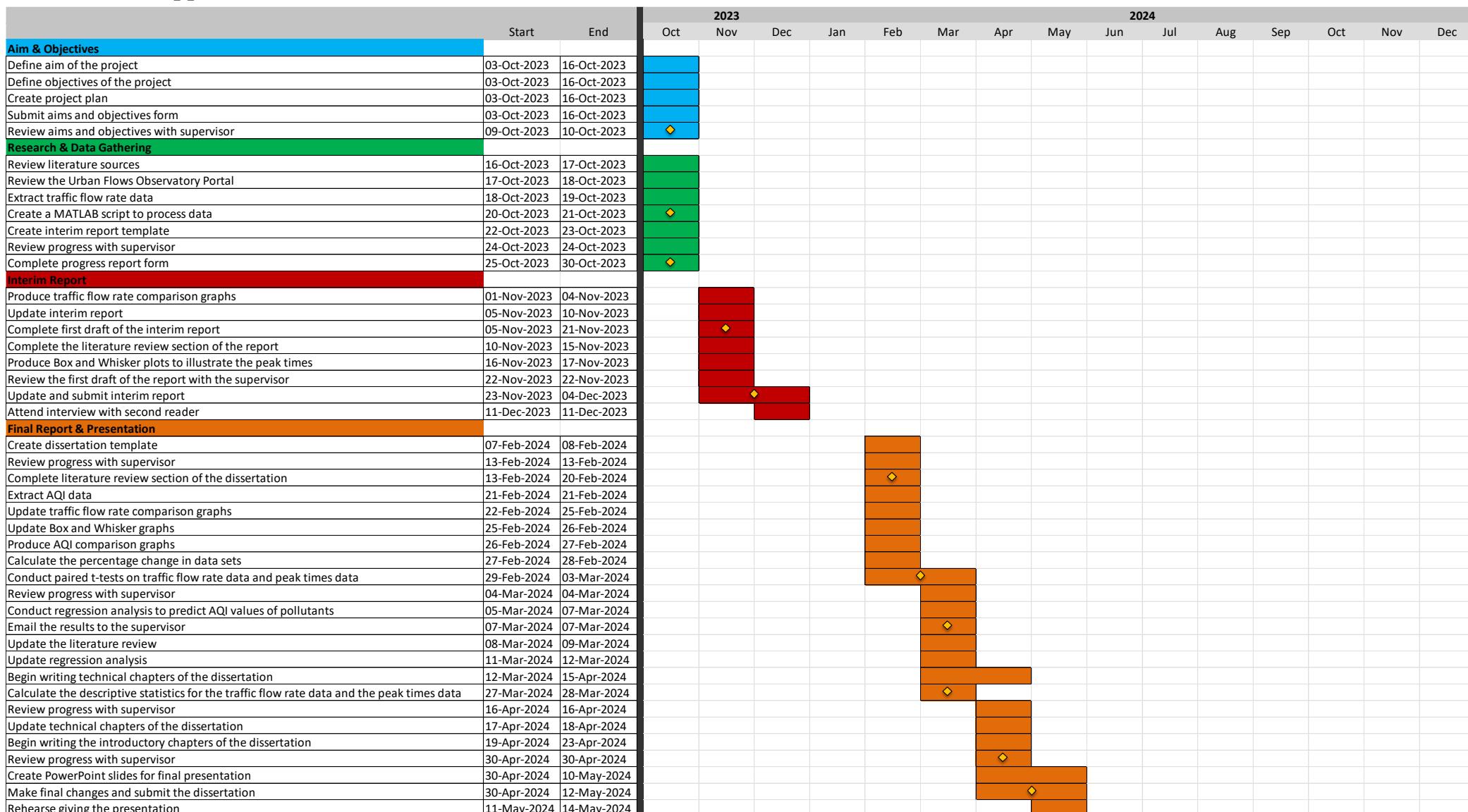
- [24] D. Muley, M. S. Ghanim, A. Mohammad, and M. Kharbeche, “Quantifying the impact of COVID–19 preventive measures on traffic in the State of Qatar”, *Transp. Policy*, vol. 103, pp. 45–59, Mar. 2021. [Online]. Available: <https://doi.org/10.1016/j.tranpol.2021.01.018>
- [25] S. R. Barnes, L. Beland, J. Huh, and D. Kim, “COVID-19 lockdown and traffic accidents: Lessons from the pandemic”, *Contemporary Econ. Policy*, vol. 40, no. 2, pp. 349–368, Jan. 2022. [Online]. Available: <https://doi.org/10.1111/coep.12562>
- [26] X. Yan and Z. Zhu, “Quantifying the impact of COVID-19 on e-bike safety in China via multi-output and clustering-based regression models”, *Plos One*, vol. 16, no. 8, Aug. 2021. [Online]. Available: <https://doi.org/10.1371/journal.pone.0256610>
- [27] A. I. Qureshi *et al.*, “Mandated societal lockdown and road traffic accidents”, *Accident Anal. & Prevention*, vol. 146, p. 105747, Oct. 2020. [Online]. Available: <https://doi.org/10.1016/j.aap.2020.105747>
- [28] W. K. M. Alhajyaseen *et al.*, “Road safety status during COVID-19 pandemic: Exploring public and road safety expert’s opinions”, *Int. J. Injury Control Saf. Promotion*, pp. 1–17, Aug. 2021. [Online]. Available: <https://doi.org/10.1080/17457300.2021.1962915>
- [29] T. Rume and S. M. D.-U. Islam, “Environmental effects of COVID-19 pandemic and potential strategies of sustainability”, *Heliyon*, vol. 6, no. 9, Sep. 2020. [Online]. Available: <https://doi.org/10.1016/j.heliyon.2020.e04965>
- [30] P. Caine. “Environmental impact of COVID-19 lockdowns seen from space.” WTTW News. <https://news.wttw.com/2020/04/02/environmental-impact-covid-19-lockdowns-seen-space> (Accessed: Feb 7, 2024).
- [31] M. Henriques. “Will Covid-19 have a lasting impact on the environment?” BBC - Homepage. <https://www.bbc.com/future/article/20200326-covid-19-the-impact-of-coronavirus-on-the-environment> (Accessed: Feb 7, 2024).
- [32] “What is nitrogen oxide and how do cars create it?” findandfundmycar.com. <https://findandfundmycar.com/articles/what-is-nitrogen-oxide-> (Accessed: Feb. 11, 2024).
- [33] “Nitrogen dioxide.” Ministry for the Environment. <https://environment.govt.nz/facts-and-science/air/air-pollutants/nitrogen-dioxide-effects-health/#:~:text=Effects%20on%20health,-The%20main%20health&text=There%20is%20also%20an%20association,It%20can%20also%20aggravate%20asthma.> (Accessed: Feb 11, 2024).

- [34] “COVID-19 and Europe’s environment: Impacts of a global pandemic.” European Environment Agency. <https://www.eea.europa.eu/publications/covid-19-and-europe-s> (Accessed: Feb 11, 2024).
- [35] C. Jones. “How did COVID-19 lockdowns affect the climate?” Met Office. <https://www.metoffice.gov.uk/research/news/2021/how-did-covid-19-lockdowns-affect-the-climate> (Accessed: Feb 14, 2024).
- [36] I. Dabbura. “K-means clustering: Algorithm, applications, evaluation methods, and drawbacks.” towards data science.). <https://towardsdatascience.com/k-means-clustering-algorithm-applications-evaluation-methods-and-drawbacks-aa03e644b48a> (Accessed: Feb. 17, 2024).
- [37] “Air quality in Europe - 2020 report.” European Environment Agency. <https://www.eea.europa.eu/publications/air-quality-in-europe-2020-report> (Accessed: Feb 20, 2024).
- [38] A. Hayes. “Descriptive statistics: Definition, overview, types, example.” Investopedia. https://www.investopedia.com/terms/d/descriptive_statistics.asp (Accessed: Mar 4, 2024).
- [39] A. D. Syafei, T. D. Irawandani, R. Boedisantoso, A. F. Assomadi, A. Slamet, and J. Hermana, “The influence of environmental conditions (vegetation, temperature, equator, and elevation) on tropospheric nitrogen dioxide in urban areas in Indonesia”, *IOP Conf. Ser.: Earth Environmental Sci.*, vol. 303, p. 012034, Aug. 2019. Accessed: Apr. 26, 2024. [Online]. Available: <https://doi.org/10.1088/1755-1315/303/1/012034>
- [40] Z. Liu, L. Shen, C. Yan, J. Du, Y. Li, and H. Zhao, “Analysis of the Influence of Precipitation and Wind on PM_{2.5} and PM₁₀ in the Atmosphere”, *Advances Meteorol.*, vol. 2020, pp. 1–13, Aug. 2020. Accessed: Apr. 26, 2024. [Online]. Available: <https://doi.org/10.1155/2020/5039613>
- [41] “AQI basics | airnow.gov.” AirNow.gov. <https://www.airnow.gov/aqi/aqi-basics/> (Accessed: Mar 19, 2024).

7. Appendix 1 – Work Breakdown Structure



8. Appendix 2 – Gantt Chart



9. Appendix 3 – Percentage Change Between the Descriptive Statistics (Peak Times)

Table 7: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the morning period in the South of Sheffield.

	Mean	Median	Variance	Standard Deviation	Maximum
Monday	-5.3%	-8.3%	-7.7%	-3.9%	-1.3%
Tuesday	-1.2%	-6.0%	+1.8%	+0.9%	-0.6%
Wednesday	+2.6%	+0.2%	+3.1%	+1.5%	+2.3%
Thursday	-8.0%	-16.1%	-3.8%	-1.9%	-1.4%
Friday	-0.1%	+2.7%	+38.3%	17.6%	+0.1%
Saturday	0%	-1.7%	-14.8%	-7.7%	+0.1%
Sunday	-4%	-5.9%	-19.7%	-10.4%	-1.9%

Table 8: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the afternoon period in the South of Sheffield.

	Mean	Median	Variance	Standard Deviation	Maximum
Monday	-1%	+1.70%	-55.60%	-33.30%	-17%
Tuesday	+2.90%	+4.70%	-42.00%	-23.80%	-1.70%
Wednesday	-0.20%	-2.80%	+107.80%	+44.10%	+21.90%
Thursday	-4.80%	-2.80%	-32.50%	-17.90%	-16%
Friday	-8.60%	-12.30%	+21.50%	+10.20%	+0.10%
Saturday	-3.30%	-4.10%	+153.90%	+59.30%	25.10%
Sunday	-1.00%	+1.40%	-30.80%	-16.80%	-11.90%

Table 9: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the morning period in the North of Sheffield.

	Mean	Median	Variance	Standard Deviation	Maximum
Monday	-5.6%	+1.3%	+127.8%	+50.9%	-10.5%
Tuesday	-8.4%	+0.2%	+125%	+50%	-4.1%
Wednesday	+0.5%	+2.7%	-71%	-46.2%	-14.1%
Thursday	-2.9%	+2.2%	-99.5%	-92.7%	-28.5%
Friday	+2.9%	+1.3%	+1308.4%	275.3%	+37.2%
Saturday	-1.8%	-2.4%	-7.5%	-3.8%	+0.1%
Sunday	-11.4%	-5.2%	+2612.7%	+420.8%	-0.6%

Table 10: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the afternoon period in the North of Sheffield.

	<u>Mean</u>	<u>Median</u>	<u>Variance</u>	<u>Standard Deviation</u>	<u>Maximum</u>
Monday	-2%	-3.8%	-12.7%	-6.6%	0%
Tuesday	+1.5%	+0.1%	+38.6%	+17.7%	+0.4%
Wednesday	-3.6%	-4.5%	-26.6%	-14.3%	-0.4%
Thursday	+4.1%	-1.6%	+22.7%	+10.8%	+4.7%
Friday	+8.5%	+5.3%	+77%	+33%	+2.8%
Saturday	-3%	-0.5%	-32.3%	-17.7%	+0.1%
Sunday	+3.7%	+2.3%	+430.9%	+130.4%	+17.8%

Table 11: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the morning period in the West of Sheffield.

	<u>Mean</u>	<u>Median</u>	<u>Variance</u>	<u>Standard Deviation</u>	<u>Maximum</u>
Monday	-22.7%	-1.8%	+754.2%	+192.3%	-4.8%
Tuesday	-21.8%	-1%	+1808.2%	+336.8%	-23.4%
Wednesday	-19.4%	-0.8%	+1403.4%	+287.7%	-22.7%
Thursday	-22.3%	-1.8%	+1337.1%	+279.1%	-17.4%
Friday	-22.1%	-0.3%	+2188%	+378.3%	-5.7%
Saturday	-19.7%	+2.5%	+3403.1%	+491.9%	+0.1%
Sunday	-23.7%	-3.7%	+6356%	+703.5%	+0.1%

Table 12: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the afternoon period in the West of Sheffield.

	<u>Mean</u>	<u>Median</u>	<u>Variance</u>	<u>Standard Deviation</u>	<u>Maximum</u>
Monday	-2.9%	-1%	+51.3%	+23%	-0.9%
Tuesday	-3.1%	+0.4%	-29.4%	-16%	-15.8%
Wednesday	-4.2%	+0.9%	-9.3%	-4.7%	-7.3%
Thursday	-5.0%	-7.4%	-7.9%	-4%	-15%
Friday	-2.5%	-3.4%	+19%	+9.1%	-8%
Saturday	+2.6%	+3.4%	+104.3%	+42.9%	+7.8%
Sunday	+2.2%	+7.1%	+60%	+26.5%	+2.5%

Table 13: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the morning period in the East of Sheffield.

	<u>Mean</u>	<u>Median</u>	<u>Variance</u>	<u>Standard Deviation</u>	<u>Maximum</u>
Monday	-6.8%	+3.1%	+108.1%	+44.2%	-1.9%
Tuesday	-7.2%	-0.8%	+110.3%	+45%	-17.4%
Wednesday	-3.9%	-1.8%	-66.4%	-42%	-9.7%
Thursday	-7.3%	-0.8%	+142.8%	+55.8%	-10.8%
Friday	0%	+1.9%	+18.3%	+8.8%	+0.9%
Saturday	-1.7%	-0.7%	+124.3%	+49.8%	-0.6%
Sunday	-0.4%	-3.2%	-34.7%	-19.2%	-0.6%

Table 14: Percentage change in the descriptive statistics between the peak times in 2019 and 2023 during the afternoon period in the East of Sheffield.

	<u>Mean</u>	<u>Median</u>	<u>Variance</u>	<u>Standard Deviation</u>	<u>Maximum</u>
Monday	+1.6%	-0.9%	-14.8%	-7.7%	-0.4%
Tuesday	-0.3%	+1.1%	-25.1%	-13.5%	-4.1%
Wednesday	+2.5%	0%	-68.4%	-43.8%	+5.3%
Thursday	-0.9%	+0.5%	-26.3%	-14.2%	-10.4%
Friday	-0.6%	+0.6%	+120.3%	+48.4%	+9.7%
Saturday	+0.2%	+2.1%	-6.5%	-3.3%	+1.9%
Sunday	-1.2%	-1.1%	+73.3%	+31.6%	+8.6%