# UNDERSTANDING FREIGHT FLUIDITY IN PEEL REGION
# WITH EMPHASIS ON ARTERIAL ROADS

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A THESIS SUBMITTED TO
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## ABSTRACT

This thesis examines the concept of freight fluidity and seeks to analyze the correlation between truck collisions and freight fluidity measures in the Region of Peel.

The study employed a multidisciplinary approach, incorporating data processing, visualization, and correlation techniques. The research involved developing a dashboard that depicts freight fluidity measures and truck collisions. A descriptive data analysis was conducted to identify trends related to freight fluidity measures and collisions. The maximum congestion for trucks was observed in the afternoon period. Brampton showed the highest level of congestion and collisions among all the municipalities.

By statistically analyzing the correlation between freight fluidity measures and truck collisions, the study provided insights into how freight fluidity can lead to safer and efficient freight transportation. A statistically significant correlation was observed between collisions and freight fluidity measures. The findings of this thesis will provide valuable insights for transportation planners in the Region of Peel.

## DEDICATION

I want to extend my deepest gratitude to my supervisor Dr. Peter Y. Park who has been a constant source of guidance and inspiration. I would also like to express my sincere appreciation to Dr. Kevin Gingerich, Dr. Mehdi Nourinejad and all my colleagues in the transportation department who have helped me along the way. Lastly, I would like to dedicate this thesis to my parents and family members who have supported me at every stage of my life.

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## LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| GIS | Geographic Information System |
| TTI | Travel Time Index |
| PTI | Planning Time Index |
| BI | Buffer Index |
| CAD | Canadian Dollars |
| GDP | Gross Domestic Product |
| US DOT | United States Department of Transportation |
| VMT | Vehicle Miles Travelled |
| et al. | et alia (and others) |
| ATRI | American Transportation Research Institute |
| HERE | HERE Technologies |
| GPS | Global Positioning System |
| DaaS | Desktop-as-a-Service |
| FPM | Freight Performance Measures |
| TRB | Transportation Research Board |
| ATT | Average Travel Time |
| TAC | Transportation Association of Canada |
| IIHS | Insurance Institute for Highway Safety |

| | |
|---|---|
| NAS | National Academy of Science |
| KPIs | Key Performance Indicators |
| ESRI | Environmental Systems Research Institute, Incorporation |
| Moran's I | Moran's Index |
| CEE | Carbon Emission Efficiency |
| GTA | Greater Toronto Area |
| FDW | Freight Data Warehouse |
| CSV | Comma-separated values |
| km/h | Kilometres per hour |
| PDO | Property Damage Only |
| PCS | Permanent Count Stations |
| PRP | Peel Regional Police |
| UC Berkeley | The University of California in Berkeley |
| H0 | Null Hypothesis |
| H1 | Alternate Hypothesis |
| AEZ | Airport Employment Zone |
| TMP | Transportation Master Plan |
| ANOVA | Analysis of Variance |

# CHAPTER 1: INTRODUCTION

This thesis assesses the efficacy of freight fluidity by testing it on arterial roads in the Region of Peel, Ontario.

## 1.1 Problem Statement

Efficient and safe movement of freight is intricately linked to the economic growth of any country and Canada, which has always been heavily involved in trade and logistics, is no exception. The growing consumer demand for goods and commodities in Canada is reflected in the 3 percent year-on-year rise in consumer spending observed between 2000 and 2019. Per capita consumer spending in Canada rose from CAD19,186 in 2000 to CAD26,410 in 2019, a 38 percent increase in 20 years (Canada Consumer Spending 1961-2022, 2022). This growing demand for consumer goods can only be fulfilled by a safe, efficient, and dependable freight delivery network.

Canada has a well-developed road network of more than 1.04 million km (Statistics Canada, 2015). The movement of goods in Canada is mainly dependent on the road network and trucks, as trucks carry approximately two-thirds of all goods by value (Canadian Trucking Alliance, 2019). The trucking industry contributes more to the Canadian GDP than air, marine and rail combined. The Canadian trucking industry in 2018 generated over CAD39 billion in revenue for the Canadian economy and created employment for over 300,000 Canadians (Placek, 2022).

In Canada, more than 48 percent of online shoppers reside in high density urban areas which makes last mile delivery by commercial trucks exceptionally challenging (Lee, Kim and Wiginton, 2019). However, our understanding of freight delivery in urban areas, especially on arterial road segments, remains inadequate. This lack of understanding is despite a disproportionate increase in vehicle miles travelled (VMT) by trucks in North America compared to passenger vehicles. Between 1993 and 2002, VMT increased by 36 percent (293.4 billion miles to 401.7 billion miles) for trucks compared to 25 percent (2.1 trillion miles to 2.6 trillion miles) for passenger cars (Transportation Research Circular, 2017). Urban truck movements in Canada are expected to increase at 3 percent per annum compared to a 2.6 percent increase for passenger cars, and roads need to be designed in a way that considers this increase in urban truck vehicle miles. Trucks and passenger cars need to be analyzed separately so that the unique characteristics and requirements of each vehicle type are accurately evaluated.

It is clearly ever more important for Transport Canada to develop an efficient and reliable freight transportation framework to support the growing Canadian logistics and supply chain network. Due to the importance of freight movement by trucks, there is a growing interest among public agencies in analyzing freight movement by trucks to make better informed decisions.

Public agencies in the Region of Peel are keen to investigate the movement of freight on arterial roads and wish to understand the implications for traffic and the road network in order to improve public investment. The Region is a prominent transportation hub in the GTA with several major highways and railway lines, and an international airport (Pearson Airport) in the area. Approximately CAD1.8 billion of goods move through the Region every day and account for 43 percent of the Region's jobs (Goods Movement Strategic Plan, 2017).

## 1.2 Freight Fluidity

Analyzing freight fluidity is a step to creating a better understanding of the Region's freight investment needs. The term freight fluidity refers to a quantitative performance measure of multi-modal supply chains in a geographic area of interest and is designed to inform decision making (Eisele and Villa, 2016). The concept of freight fluidity was first popularized by Transport Canada to quantify and assess the performance of multi-modal supply chains and key commercial freight corridors across Canada, and Transport Canada has been credited with developing freight fluidity measures (Eisele et al., 2016; Russell, 2014; and Lyman and Bertini, 2008). Freight fluidity is used to identify constraints in a freight network by quantifying system performance through measures and indicators. Freight fluidity uses measures of travel time and reliability to assess performance along a defined freight network. For example, the observed travel time values compared with free flow travel time (without any impedance to flow of traffic) can be used to estimate delays in a freight network. Simply put, freight fluidity, enables us to evaluate the performance of a given freight transportation network by conducting an evidence-based analysis of its reliability and overall performance.

Freight fluidity refers to the smooth, efficient, and uninterrupted movement of goods through the various stages of the transportation and logistics network. It involves optimizing the flow of goods from its point of origin to the final destination, minimizing delays and congestion, and ensuring seamless transitions across different modes of transportation. In recent years, the concept of freight fluidity has become increasingly important, especially in the context of multi-modal supply chain networks. Transporting cargo from seaports via trucks to the end customer is critical for seamless freight transportation. Transport Canada has been actively adopting and investing in various measures at improve fluidity within its operations of multi-modal supply chain network (Transport Canada, 2022). Achieving integrated intermodal connectivity plays a crucial role in reducing transit times and mitigating congestion, thus significantly enhancing the efficiency of the entire supply chain. This holistic approach is key to ensuring timely deliveries and boosts economic competitiveness in the global logistics network. Freight fluidity measures are used to:

1. Provide transparent and reliable information pertaining to freight network in a particular geographical area;
2. Identify trends in the freight logistics network; and
3. Facilitate consistent comparison of roadways (Hoel et al., 2021).

The measures estimate the performance of a freight network by considering unexpected delays and allow us to identify areas that experience congestion and delays. The data generated are used to help delivery companies to plan accordingly.

Despite advancements in technology and safety procedures, truck collisions are a major issue. A truck collision may involve another truck and/or vehicle, pedestrian, or cyclist. The severity of a collision ranges from property damage only (PDO) collisions to collisions that involve an injury to collisions that involve a fatality. Due to the size and weight of trucks, truck collisions may have particularly severe consequences.

Decision makers in Canada rely upon a variety of data sources to study and monitor freight mobility and safety. These datasets mainly consist of information on truck volumes, freight corridors, turning movement counts at intersections, collisions, and congestion hotspots. The datasets are often obtained from multiple sources and need to be combined and processed before they can be used for making decisions (Turner, 2004). Although existing tools and platforms can be leveraged to gain insights into freight mobility and safety, advancements in data collection and analysis have led to the development of visualization platforms that can make the data-driven decision process more efficient and streamlined. For example, the development of specialized dashboards for freight fluidity analysis could play a valuable role in analyzing and improving freight fluidity. A dashboard is a visual tool that facilitates the representation of data (for example, information about freight movement based on road characteristics) in a concise and easily understandable format. There is growing interest among decision makers in dashboards that incorporate data from multiple sources to facilitate proactive decision making (US Department of Transportation, 2021). Transportation agencies in Canada currently lack such a tool.

Although studies designed to help decision makers make better informed decisions have shown, for example, that there is a positive relation between congestion and pollution (Currie and Walker, 2011; Bigazzi and Figliozzi, 2013; Bel and Rosell, 2013; Beaudoin et al., 2015 and Simeonova et al., 2018), there is a notable absence of empirical studies exploring the relationship between freight fluidity measures and collisions (Albalate and Fageda, 2021).

### 1.3 Study Goals and Objectives

The goal of this research on the Region of Peel’s road network is twofold: to estimate freight fluidity and investigate the relationship between collisions and freight fluidity measures; and to develop a visualization tool which can be used by decision makers in the Region for making informed decisions in the realm of freight transportation.

The research has four objectives:

1. Identify the most appropriate freight fluidity measures and quantitatively estimate freight fluidity measures for the study area's arterial roads.
2. Collect data on collisions involving trucks and conduct a statistical investigation into the spatial association between freight fluidity measures and truck collisions.
3. Conduct a descriptive statistical analysis of freight fluidity measures and truck collisions to gain insights into the spatial patterns and temporal trends of truck travels in the Region of Peel.
4. Create a user-friendly geospatial interactive platform using ArcGIS Pro to display the most congestion and collision prone corridors in the Region of Peel based on the identified freight fluidity measures.

Figure 1-1 below shows the research objectives in relation to the corresponding thesis chapters.

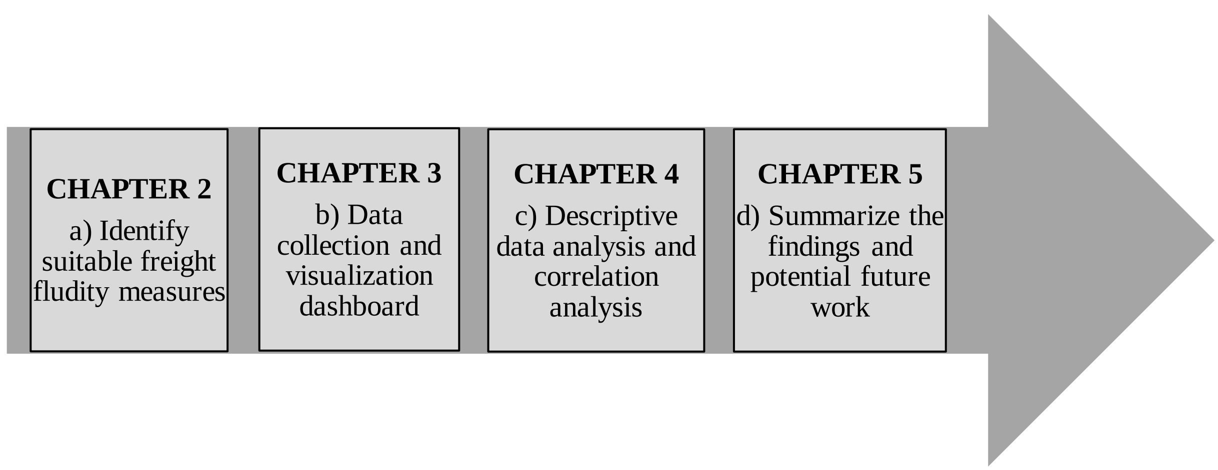



Figure 1-1: Relation between research objectives and thesis chapters

## 1.4 Structure of Thesis

This research consists of five chapters, including the current *Chapter 1: Introduction*. *Chapter 2: Literature Review*, summarizes existing work pertaining to freight fluidity. The primary focus of this chapter is to synthesize existing knowledge related to freight fluidity measures and collisions as well as any associations between them. *Chapter 3: Study Area, Data and Dashboard* focuses on understanding the study area and data pertaining to freight fluidity in the Region of Peel. The dashboard describes the intricacies of the visualization platform developed in this research. *Chapter 4: Analysis Results*, summarizes and discusses the descriptive analysis and the statistical analysis. The relationship between freight fluidity measures and truck collisions is also discussed in this chapter. *Chapter 5: Conclusions* highlights the key findings and contributions of this research. The chapter also discusses the potential for future work.

## 1.5 Study Scope

The research considers arterial roads in the Region of Peel. Both major and minor arterial roads are analyzed in this study. Freeways and local roads are not included. Figure 1-2 shows the arterial roads considered in this research. A macroscopic analysis has been conducted that analyzes all the arterial roads in the Region of Peel. The analysis provides a holistic understanding of the system by identifying overarching patterns and insights and provides a comprehensive analysis of the entire Region of Peel. A specific segment-level analysis is not the primary focus of this research.

The study analyzes mobility and safety issues using 2019 and 2020 data supplied by the Region of Peel. These two years of data were chosen deliberately to compare and contrast the 'pre-pandemic' and 'during pandemic' traffic flows and safety. In addition to the 2019 and 2020 collision data, collision data for 2018 were included in the descriptive analysis in order to account for any bias caused by implementation of the ‘Vision Zero Road Safety Strategic Plan’ by the Region of Peel in September 2018 (Vision Zero, 2018). The 2018 truck collision data provides a baseline to help identify the changes brought about by a particular intervention, in this case the implementation of ‘Vision Zero Road Safety Strategic Plan' in the Region of Peel, on truck collisions in subsequent years.

The study uses freight fluidity measures presented in past studies. The study does not aim to develop a new freight fluidity measure. The safety data analysis is therefore limited to travel time (estimated from speed), collision type, collision severity and collision location. Other possibly important safety factors, such as driver behaviour and vehicle characteristics, are not included in the analysis.

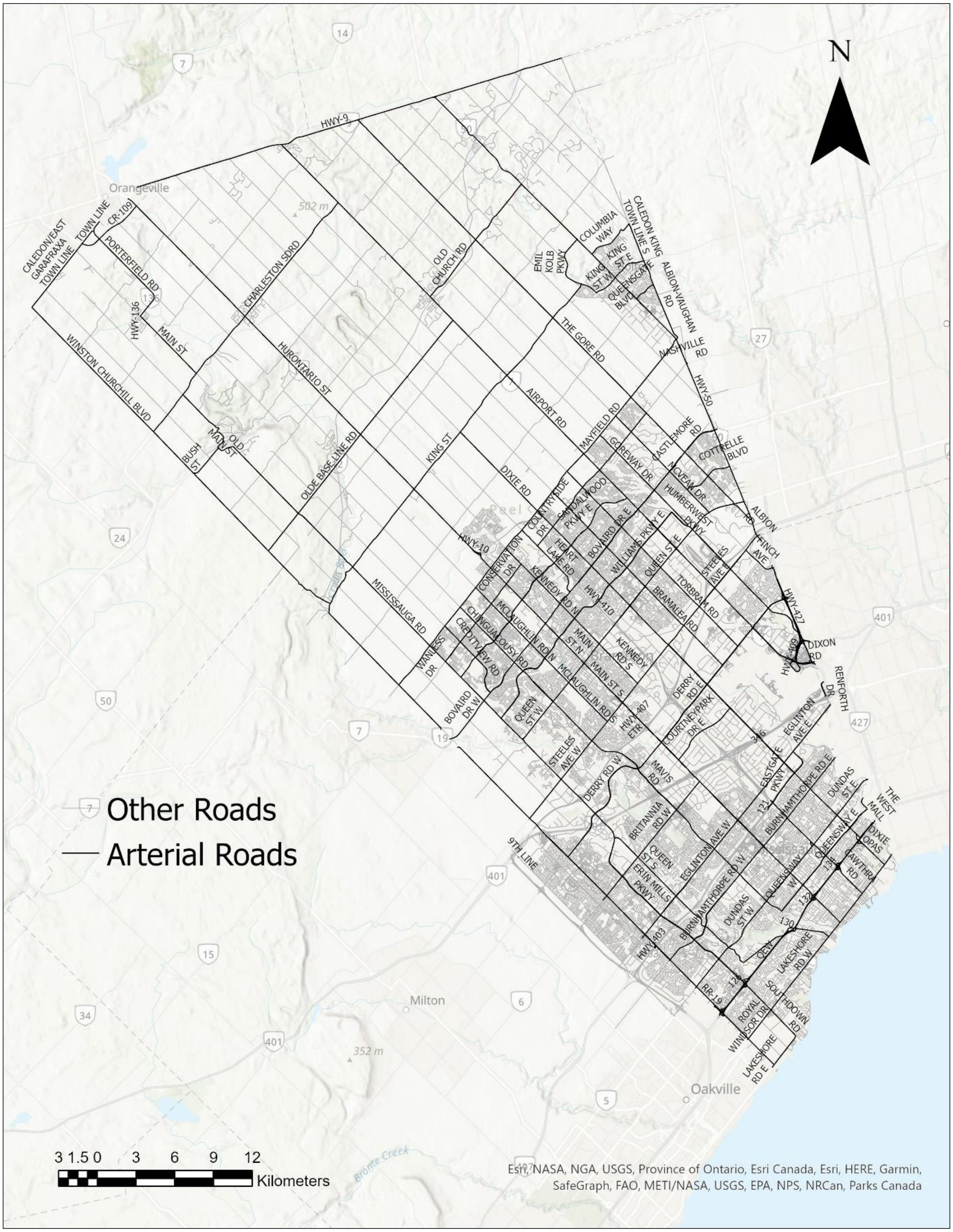



Figure 1-2: Road Classification in Region of Peel

# CHAPTER 2: LITERATURE REVIEW

The literature review considers roadway type and segmentation, freight fluidity, freight safety, the relationship between collisions involving with trucks and mobility, and visualization tools. The review concludes with a discussion of the limitations in literature and the potential for future studies.

## 2.1 Roadway Type and Segmentation

The road network, including the road type such as freeway or arterial, plays an important role in evaluating freight fluidity. All the previous known research focuses on evaluating freeways when analyzing freight fluidity. There is limited research emphasizing freight fluidity on arterial roads. Assessing the differences between freeways and arterials is essential to account for the differences in the traffic flow, design, and speed, when evaluating freight fluidity. Matching freight fluidity to the right type of roadway can lead to more robust analysis.

There are some commonalities in evaluating freight fluidity on freeways and arterial roads. Firstly, both freeways and arterials use travel time as a measure to identify congestion. Travel times resonate well with the general public as they are easy to communicate and comprehend (Margiotta et al., 2015). Secondly, both freeways and arterial roads use a ranking system from worst to best to identify bottleneck locations. (Chimba, 2020). However, there are explicit differences in evaluating freight fluidity for freeways and arterial roads.

The segmentation criteria used to analyze freight fluidity for freeways and arterial roads differ. Freeways consist of longer segment lengths, typically in the range of 10 to 20 km. Shorter segment lengths are used for analyzing arterial roads. Arterial segment lengths ranging between

3 to 5 km are common, and can be as short as 1 km in areas with high traffic density (Zhao and Venkatanarayana, 2019).

The reference speed used for evaluating freight fluidity measures differs between freeways and arterial roads. Reference speed refers to the highest recommended speed at which a vehicle is expected to operate in a safe and efficient manner, taking into account the regulatory requirements of a jurisdiction (Wan et al., 2016). Freeways generally have long corridors with relatively consistent posted speed limits. Freight fluidity analysis usually uses posted speed limits as refence speeds for freeways. Arterial roads have greater variations in posted speed limit and changes in the speed limit may be frequent. Reference speed is typically based on the $85^{th}$ percentile speed observed on an arterial road (Margiotta et al., 2015).

Freeways generally have higher speeds and fewer access points compared to arterials roads. Arterial roads generally consist of intersections, traffic signals and pedestrian crossings, which can make data collection complex. Freeways tend to have a consistent and predictable flow of traffic with fewer disruptions, allowing for more continuous data collection. This makes it easier to collect data on freeways compared to arterial roads. Nevertheless, advancements in technology have greatly contributed to making data collection on arterial roads highly reliable and accurate. Arterial roads usually have numerous access points and numerous possible locations for installing sensors to collect speed and volume data. We can also use probe vehicles equipped with GPS devices and other sensors to collect real-time data (Sun et al., 2009). Previous studies have mostly focused on peak time periods for analyzing freeways, but agencies such as HERE Technologies and American Transportation Research Institute (ATRI) can measure and update real-time data on arterial roads for the entire 24-hour day (ATRI, 2023).

There is limited research that specifically focuses on freight fluidity on arterial roads. As there is no known baseline that explicitly defines a particular time period for analyzing freight fluidity on arterial roads, this study's focus on the entire 24-hour period could help to develop a more comprehensive understanding of transportation patterns and trends without missing out on any relevant time periods.

## 2.2 Freight Fluidity Data and Measures

Freight fluidity is a function of various factors including mobility, road type, freight demand and supply, and logistics. The US Department of Transportation (USDOT) identifies mobility as one of the dominant factors causing delays in freight transportation (USDOT, 2015). Analyzing freight fluidity can help reduce costs and enhance logistics efficiency. As freight fluidity plays a vital role in the efficient and smooth movement of goods through transportation networks, the analysis of the freight fluidity of a transportation network can help to bolster economic growth and facilitate trade by minimizing delays and cost.

Delays in logistics can be broadly categorized as expected delays and unexpected. Expected delays in freight transportation, such as periodically reoccurring congestion during peak hours, scheduled maintenance, and regulatory checks, are planned for and accounted for in logistics operations. While freight fluidity measures may not directly influence maintenance and regulatory checks, they play a crucial role in mitigating the impact of these expected delays by optimizing routes and enhancing overall supply chain efficiency. In contrast, unexpected delays refer to unforeseen disruptions that can significantly affect the movement of goods. These include factors such as collisions, adverse weather conditions, or sudden changes in traffic demand. Another example of an unexpected delay is the unforeseen increase in online purchasing witnessed during the pandemic (Tardif, 2021). Such instances can cause a rapid increase in induced demand, disrupting the fluid movement of goods. Freight fluidity measures can help address these unexpected delays by providing predictive analytics, logistics tracking, and mitigation strategies to minimize their impact on the supply chain. In a country like Canada, which relies heavily on trade, the concept of freight fluidity is essential for strengthening economic growth and commerce by minimizing logistics delays.

Freight fluidity focuses on calculating metrics for individual freight corridors in a road network. Freight fluidity measures require data related to spatial and temporal variation in travel time on a road segment (Pulugurtha et al., 2015). There are various ways of collecting freight fluidity data.

Global Positioning System (GPS) is a navigation tool that can be used to estimate travel time and delays. GPS can be used to record spatial coordinates through the floating car technique where a car mounted with GPS antennae drives through the road network and collects data. However, this technique requires a large sampling rate and can also be influenced by positional bias (Hong and Vonderohe, 2011).

Bluetooth detection is another technique that allows devices to exchange data over short distances. Bluetooth detection consists of a unique identifier that is transmitted by a device to record data pertaining to distance covered over a period of time. It is a cost-effective technique of continuous data collection. The accuracy of data increases with reduced vehicle speeds and increased distance between detectors (Haghani et al., 2010). However, the data can become distorted by non-uniform traffic flow and by signal delay.

INRIX is a Desktop-as-a-Service (DaaS) company which monitors more than 260,000 miles of road network in real time. The data are mainly used for analysis at a macroscopic level. The company uses proprietary big data techniques to obtain the data. Although the data are updated every minute, past research has found the data to be effective only for corridor level analysis (Pulugurtha et al., 2015). Hence, the data could be used for freeway analysis, but would not be sufficiently accurate for arterial roads.

HERE Technologies is a world leader in traffic mapping and location-based services, providing geo-spatial data for over 200 countries. The company employs a suite of data sources including probe data, sensor data and historical data for generating travel time at 5-minute intervals (Turner et al., 2011).

The American Transportation Research Institute (ATRI) Freight Performance Measures (FPM) program regards Travel Time Index (TTI), Planning Time Index (PTI) and Buffer Index (BI) as the most important freight fluidity measures as they encapsulate travel time and reliability (ATRI, 2021). Freight fluidity measures are essential for enhancing the efficiency and reliability of freight movement within supply chains. The field of freight transportation offers a range of existing fluidity measures and indicators, each tailored to address specific aspects of operational efficiency. These measures aim to improve the reliability of freight movement, optimize routing and scheduling, and reduce the impact of unpredictable factors in freight transportation. By adopting and refining these measures, stakeholders in the freight transportation industry can make informed decisions to streamline operations and minimize disruptions.

Additional existing freight fluidity measures include Queue Length, Spillback, Delay, 80th percentile Travel Time Index (TTI), and Average Travel Time. These five measures are summarized below:

1. *Queue Length* $(L_q) = \lambda H$ [Equation 1]

   Where:

   $L_q$ represents the queue length, measured by the number of vehicles.

   $\lambda$ represents the vehicle arrival rate, measured by vehicles per second.

   H represents the average headway of vehicles, measured by seconds.

   Queue Length ($L_q$) is a mobility measure that indicates the distance from the stop line to the tail of the last vehicle halted in traffic (Roess et al., 2011). Previous studies primarily used segment-level shapefile data for calculating $L_q$. One advantage of $L_q$ is its ability to identify congested areas at intersections. However, $L_q$ mainly focuses on immediate congestion at a specific location and may not capture broader traffic flow dynamics, travel pattern variations, or external factors affecting congestion. Because $L_q$ is dependent on the segment length used in the network, longer segments may look worse compared to shorter segments (Zhao and Venkatanarayana, 2019). This reduces the usefulness of $L_q$ for evaluating mobility (Ni, 2015).

2. *Spillback* $(X_{spill}) = \frac{q}{k} \cdot T_{delay}$ [Equation 2]

   Where:

   $X_{spill}$ measures vehicle spillback in meters.

q is the vehicle flow rate, in vehicles per second.

k is the vehicle density, in vehicles per meter.

$T_{delay}$ is the delay at the congested location, in seconds.

Spillback ($X_{spill}$) indicates how far the vehicles extend beyond a stop point and into the previous intersections or road segments (Mohajerpoor et al., 2019). Vehicle volume data is typically used to estimate $X_{spill}$. It is useful for identifying bottlenecks and assessing the impact of any road modifications. However, $X_{spill}$ values can be misleading if signal timings are not considered. $X_{spill}$ can be reduced by up to 28 percent if optimal signal timings are implemented (Mohajerpoor and Cai, 2020). The heavy influence of signal timing makes $X_{spill}$ a less reliable mobility measure (Han and Gayah, 2015).

3. $Delay\ (D) = V.\ max\left(0, \left(\frac{L}{S} - \frac{L}{Ref\ S}\right)\right)$ [Equation 3]

Where:

D measures the delay experienced by vehicles in vehicle hours.

L is the segment length, in kilometers.

V is the vehicle volume, in the number of vehicles.

S is the average speed, in kilometers per hour.

Ref S is the reference or free flow speed, in kilometers per hour.

Delay (D) quantifies the time lost by drivers by measuring the additional travel time compared to travel time at the reference speed for the volume of traffic observed on a road network (Jha and Eisele, 2015). Vehicle volume and reference speed data are required for estimating D. The measure provides a numerical estimate that can be tracked and compared over time, helping assess changes in mobility performance. However, setting an acceptable threshold for D can be subjective and vary by context and stakeholder perspectives, reducing its use as a mobility analysis tool (Margiotta et al., 2015).

4. $$80th\ Percentile\ TTI\ (80th\ TTI) = \frac{80th\ Percentile\ Travel\ Time}{Freeflow\ Travel\ Time} \qquad \text{[Equation 4]}$$

   80th Percentile Travel Time Index (80th TTI) measures the travel times experienced by the 80th percentile of drivers (Transportation Research Board, 2021). It is a ratio based on segment-level travel time data for a road network, without units. The index is a variation of TTI and measures the time taken for 80 percent of trips. While 80th TTI is an additional measure, the industry standards often recommend using Travel Time Index (TTI) or Planning Time Index (PTI) for a more accurate reflection of typical journey times (Zhao and Venkatanarayana, 2019).

5. $$Average\ Travel\ Time\ (ATT) = \frac{L}{S_{mean}} \qquad \text{[Equation 5]}$$

   Where:

   ATT is the average travel time to traverse a roadway section, in hours.

   L is the segment length, in kilometers.

   $S_{mean}$ is the average speed, in kilometers per hour.

Average Travel Time (ATT) evaluates the movement efficiency of goods from origin to destination in a roadway network. It is calculated by estimating the travel time for a given road segment (Jalali, 2020). This approach provides a basis for comparing the network’s ATT to established benchmarks and evaluating the efficiency of the transportation network. Segment level travel time data at a pre-defined interval are needed to estimate ATT. Monitoring ATT helps identify bottlenecks or congested areas, aiding transportation planning and road infrastructure investment decisions. However, ATT does not account for travel time variability or dispersion and can be influenced by outliers (Duvvuri and S. S. Pulugurtha, 2021).

It is evident that each of the five measures discussed varies in the type of data used and has its own set of advantages and disadvantages. The three main freight fluidity measures are Travel Time Index (TTI), Planning Time Index (PTI) and Buffer Index (BI). These measures provide a more comprehensive insight into travel time reliability, user experience, and planning considerations. They provide valuable estimates for real-time decision-making, reliability assessment and long-term planning, and allow for a holistic understanding of mobility challenges and potential solutions.

The three measures are discussed below:

a) $$Travel\ Time\ Index = \frac{Average\ Travel\ Time}{Freeflow\ Travel\ Time}$$ [Equation 6]

Travel Time Index (TTI) measures the additional time required to reach the destination under average traffic conditions in comparison to free-flow travel time. TTI can be estimated for various time periods (such as daily, weekly or monthly) to understand and compare the variations. There is a direct relationship between TTI and congestion. The higher the value of TTI, the more congested is the network.

b) $$Planning\ Time\ Index = \frac{95th\ Percentile\ Travel\ Time}{Freeflow\ Travel\ Time}$$ [Equation 7]

Planning Time Index (PTI) refers to the time required to reach the destination 95 percent of the time in relation to free-flow travel time. It is mainly used for urgent shipping deliveries such as refrigerated goods. PTI has a value greater than or equal to TTI. PTI also has a direct relationship with congestion. The higher the value of PTI, the more congested is the network.

c) $$Buffer\ Index = \frac{95th\ Percentile\ Travel\ Time - Average\ Travel\ Time}{Average\ Travel\ Time}$$ [Equation 8]

Buffer Index (BI) is used to estimate the time cushion, i.e., the extra time required to reach the destination on time 95 percent of the time in comparison to average travel time. BI represents a near worst-case scenario (the $95^{th}$ percentile travel time) and takes into account unexpected delays. As is the case for TTI and PTI, BI also has a direct relationship with congestion. The higher the value of BI, the more congested is the network.

TTI, PTI and BI are ratios which negate the effect of segment lengths, which is important especially for arterial roads. Freight fluidity measures such as queue length, spillback and delay are less reliable and accurate for freight fluidity analysis because they are affected by segment length.

TTI enables comparisons of travel times across different time periods and locations. It helps identify trends, patterns, and areas of concern, facilitating the evaluation of the effectiveness of transportation interventions or infrastructure improvements over time. PTI can help provide insights for long-term transportation planning. It considers the impact of infrastructure investments, land-use decisions, and policy changes on travel times. BI takes into account the impact of external factors such as incidents, weather conditions, or other disruptions, on travel times. It provides a measure of the predictability and consistency of travel times, which is critical for planning and decision-making (Eisele et al., 2016; Russell, 2014; and Lyman and Bertini, 2008).

TTI, PTI and BI provide robust metrics that can be used to assess and communicate the impact of congestion and facilitate comparison. This research therefore focuses primarily on TTI, PTI and BI for analyzing freight fluidity on arterial roads.

## 2.3 Freight Safety

In 2020, 139,722 vehicles (of all types) were involved in collisions across Canada. The collisions were suffered by almost 27 million licensed drivers on Canadian roads, costing the Canadian GDP nearly CAD36 billion, the equivalent of CAD946.65 per capita (Transport Canada, 2023). Trucks were involved in approximately 10,038 of the 2020 collisions with 4,637 injuries and 317 fatalities. These statistics are calculated using data from the Transport Canada National Collision Database (National Collision Database, 2023).

In 2021, Canada saw 1,768 motor vehicle (of all types) fatalities (a 1.3 percent increase from 2020), and 108,018 injuries (a 3.6 percent increase from 2020). Fatalities per 100,000 population increased from 4.6 in 2020 to 4.7 in 2021 (Transport Canada, 2023). Among these collisions, 379 fatal collisions involved trucks. This was a 20 percent increase over 2020. Urban areas accounted for 73 percent of truck collisions and 45 percent of fatalities (Government of Canada, 2023). Almost half of all fatalities involving trucks in North America in 2021 occurred on arterial roads (48 percent). Freeways saw 36 percent of truck fatalities while the remaining 16 percent occurred on collector and local roads (IIHS, 2023). As arterial roads contributed to almost half of all truck related fatalities, it is important to emphasize collisions on arterial roads.

A study conducted in Canada from 2013 to 2017 suggested that prior knowledge about road characteristics, including congestion and delay, can be a significant contributor in reducing truck collisions. The study highlighted the need for analyzing mobility and safety concurrently to help reduce the frequency of truck collisions (Singh, Guo and Wang, 2020).

This research focuses on both mobility (via freight fluidity measures) and safety (via truck collisions) to obtain a holistic understanding of the arterial road network in the Region of Peel that can help provide efficient and safe mobility for all road users.

Peel Region has adopted Vision Zero to enhance road safety (Region of Peel, 2018). In September 2018, the Peel Region Council introduced the 'Vision Zero Road Safety Strategic Plan' with the objective of minimizing motor vehicle collisions in the Region. Vision Zero provides a framework to avoid injuries and fatalities on roads by enhancing coordination among agencies. The motto of Vision Zero is "No loss of life is acceptable" (Kim et al., 2017). Peel Region is committed to reducing collisions by 10 percent in the short term (Region of Peel, 2018). However, this target includes all modes of transportation and does not provide a specific target for trucks. Ensuring truck safety on arterial roads has become a significant concern. According to the '2020 Vision Zero Road Safety Strategic Plan Update – Year Three,' the total number of collisions in Region of Peel involving all modes remained constant from 2017 to 2019 and showed a sharp decline in 2020 (pandemic year) (Region of Peel, 2021). The total number of collisions from 2017 to 2019 remained constant at approximately 6,000 collisions and decreased by 30 percent to around 4,000 collisions in 2020 (Region of Peel, 2021). However, the percentage of collisions involving trucks remained at 6 percent from 2017 to 2019 and increased to 7 percent in 2020 (Region of Peel, 2021). The rise in the proportion of collisions involving trucks is a matter of concern and emphasizes the importance of analyzing truck safety in the Region of Peel.

## 2.4 Relationship between Collisions Involving Trucks and Mobility

The interaction between collisions and mobility is essential to understanding sustainable freight transportation, especially in urban environments (Albalate, and Fageda, 2021). In the realm of transportation, freight fluidity is a subset within the mobility measures. Mobility measures include a variety of metrics that focus on analyzing the efficiency, accessibility, and effectiveness of transportation systems. The metrics provide a quantitative numeric value that helps to understand the movement of people, goods and services. Freight fluidity is a significant component of this broader framework and is mainly focused on analyzing the flow of freight across transportation networks (Kruse et al., 2018).

Mobility measures such as speed, traffic density, volume and VMT have a significant impact on the time and cost of travel. Long travel times and high costs are generally associated with low levels of mobility. Similarly, a high number of collisions is generally perceived as a low level of road safety (National Academy of Science, 2023). High traffic volumes and high speeds are associated with an increase in the number and severity of collisions. Although both mobility and collisions affect the road user experience, prior studies have not specifically focused on urban arterial roads, leaving a gap in our understanding that suggests a statistical association between mobility and collisions on urban arterial roads (Wang et al., 2013).

Several studies have attempted to establish a relationship between mobility and collisions, but there is a scarcity of research specifically investigating the relationship involving trucks. Most existing studies encompass mobility across all transportation modes. For instance, a 2018 study in the United States indicated a positive correlation between vehicle miles traveled (VMT) and collisions, but this VMT was not truck-specific and included all modes of transportation. The study by Fitzpatrick et al., 2018, also highlighted that factors like road design, driver behavior, and traffic volume might have influenced the high collision rates. (Fitzpatrick et al., 2018).

In Europe, research spanning from 2008 to 2017 across 130 cities examined the connection between congestion and collisions. This research included all modes of transportation and was not explicit regarding trucks. The results of this research indicated a non-linear relation between congestion and safety, suggesting that roads are safer in less congested cities (Albalate and Fageda, 2021). However, the study suggested that high traffic density combined with narrow streets in many European cities increased exposure to collisions. Nevertheless, the associated collisions had a reduced severity due to slower speeds. The findings were inconclusive and varied based on the data and analysis method used (Albalate and Fageda, 2021).

Overall, the literature suggests that the relationship between mobility and collisions is complex and depends on a multitude of factors and nuances. While some studies indicate a relationship between collisions and mobility, others do not find definitive evidence of such a link. The specific relationship between mobility and truck collisions is particularly unclear, especially for trucks in urban areas.

There are some statistical methods that can be deployed to examine the correlation between mobility measures and collisions. Pearson's correlation is one such statistical method used to study the statistical association between two variables. There are other correlation methods (e.g., Kendall's Rank Correlation) but Pearson's correlation is the most widely used statistical technique for studying both the level of association and the direction of the relationship between two variables (Profillidis and Botzoris, 2019). Pearson's correlation has been used to develop an accurate and reliable prediction of traffic congestion during the Covid-19 pandemic (Gamel et al., 2023). It has also been used to estimate the correlation between urban traffic patterns and the population distribution of urban residents (Chen et al., 2020). The use of Pearson's correlation to study the statistical association (if any) between collisions and mobility can facilitate the development of constructive traffic management and control strategies.

### 2.5 Visualization Tools

The visualization of a transportation problem helps to convert a complicated mathematical model into a clear, comprehensible, and easy to understand depiction. Simplifying complex information and illustrating it visually helps decision-makers make informed and effective decisions in a more efficient manner. There are several options available for illustrating freight fluidity measures and collision data in a visual format. Each platform has its own set of advantages and disadvantages.

Tableau is a visual analytics platform, currently operated by Salesforce Inc., to help businesses identify patterns and trends. Tableau can handle and interact with large datasets using filters, slicers, and drill-down tools. These functionalities make it user friendly even for non-technical users. However, Tableau does not allow data cleaning and data transformation. It has limited functionality in creating dashboards and is complex to set up.

MS Excel, developed by Microsoft, is one of the most widely used spreadsheet programs. It allows numerical analysis of data using formulae and functions. Excel is intuitive and user friendly. It provides tools for charting and graphing, including pivot tables for complex datasets. However, Excel has limitations in handling large datasets and cannot handle more than

1,048,576 rows of data. It does not have the functionality to create dashboards or handle complex data visualizations.

Looker Studio, previously known as Google Data Studio, is a web-based visualization tool developed by Google to track KPIs, visualize trends and compare performances. It is capable of real time data analysis. It is scalable and can handle large datasets. Looker Studio transforms data into customizable reports and dashboards that allow users to make better informed decisions. However, the software is costly and the price increases with increased usage. Looker Studio is a cloud-based platform which can lead to data security concerns, especially for confidential traffic data. In addition, it has limited options for customization.

QlikView is a business intelligence platform used for data translation. The platform was built by a Swedish company called Qlik in 1994. QlikView can connect to a variety of data sources including databases, cloud services and spreadsheets. It uses in-built processor memory to speed up data analysis. However, QlikView has a steep learning curve for someone new to data analytics. It is also marred by privacy and data breach issues. The mobile version is less comprehensive than the desktop version, which limits its usage.

ArcGIS Pro is a Geographic Information System (GIS) software developed by Esri for creating, managing, and analyzing spatial data. It is easy to navigate and provides specialized tools for network analysis and geo-statistics. The interface can be integrated with other Esri products such as Dashboards, Network Analyst and StoryMaps. It is intuitive and user friendly and can handle large datasets. However, ArcGIS Pro has high system requirements, especially for large complex projects which can be a hindrance for less powerful computers.

After considering the options available, ArcGIS Pro was chosen for conducting the visualization and creating the dashboard in this research.

Dashboards are a useful tool in transportation studies by providing a visual depiction of complex data, in an easy to understand format. The use of dashboards in transportation studies has evolved over time in Canada, with a focus on improving mobility and enhancing safety. Some of the most prominent dashboards developed in Ontario for transportation analysis include:

1. Figure 2-1 (a) features an example of the Ministry of Transportation (MTO) iCorridor dashboard. Launched in 2013, the iCorridor dashboard aims to support data analytics, visualization, and transportation planning. It includes a variety information such as population density, mode share, and performance characteristics, aiding in transportation planning decisions. The latest fourth generation iCorridor dashboard is hosted on the ArcGIS Pro platform and uses a range of data sources, such as the Census data, HERE data, Waze Traffic data, and the Transportation Tomorrow Survey data (Ministry of Transportation, 2023).
2. Figure 2-1 (b) and (c) show examples of the Region of Peel collision dashboards. Developed by the Peel Data Centre in 2022, these dashboards support the Region's Vision Zero initiatives. They provide a detailed visualization of traffic collisions in the Region of Peel, categorizing incidents by transportation modes and specific driver behaviors, such as cyclists, pedestrians, and impaired driving. The dashboards incorporate HERE data and other historical collision data and are developed on the ArcGIS Pro platform (Region of Peel, 2023).

3. Figure 2-1 (d) shows an example of the Toronto Police Service dashboard, which offers information on fatal traffic collisions. Based on historical data obtained from Toronto Police Service and City of Toronto Transportation Services, this dashboard is regularly updated within 1-2 business days following a fatality. The dashboard is hosted on ArcGIS Pro platform, and it includes collision data from 2006 onwards (Toronto Police Service, 2023).

The growth popularity of dashboards in the transportation sector is evident, thanks to their user-friendliness and easy comprehensibility. The ArcGIS Pro platform is known for its robust geospatial capabilities and seamless GIS Data integration. Thus, the dashboard developed as a part of this study is also intricately hosted within the ArcGIS Pro platform.

Figure 2-1 shows the snippets of some of the collision and mobility dashboards developed to analyze transportation in Ontario.

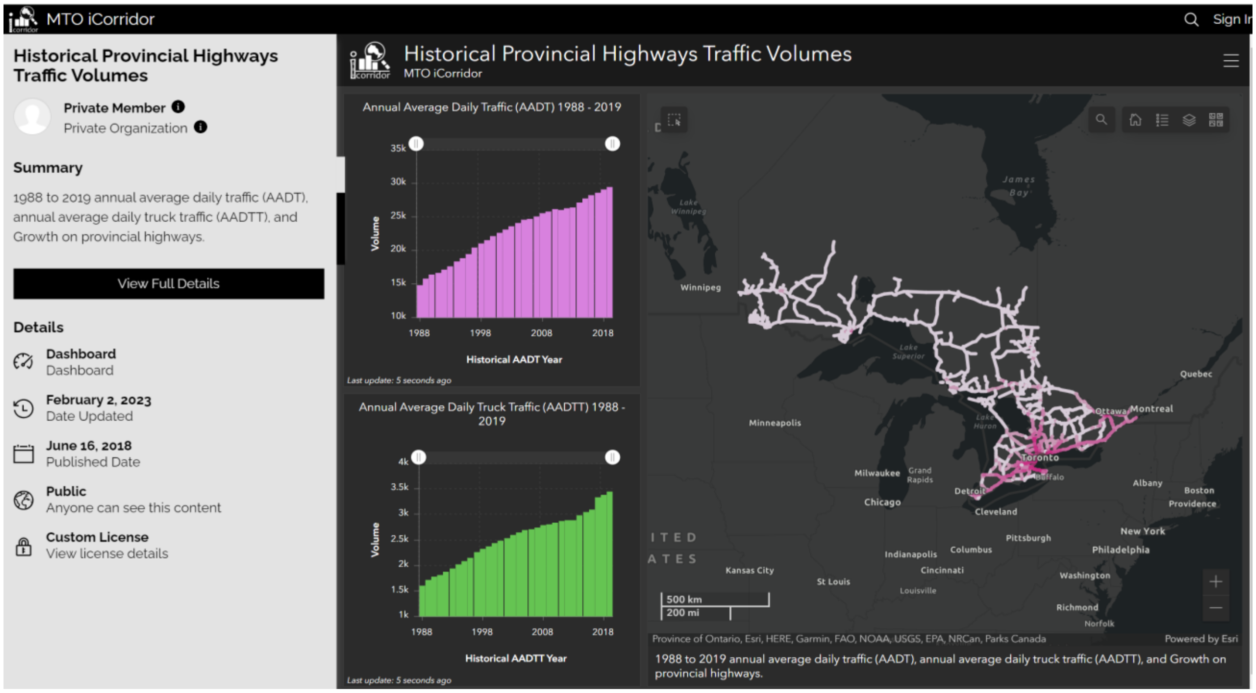



Figure 2-1 (a): Existing transportation dashboards - MTO iCorridor

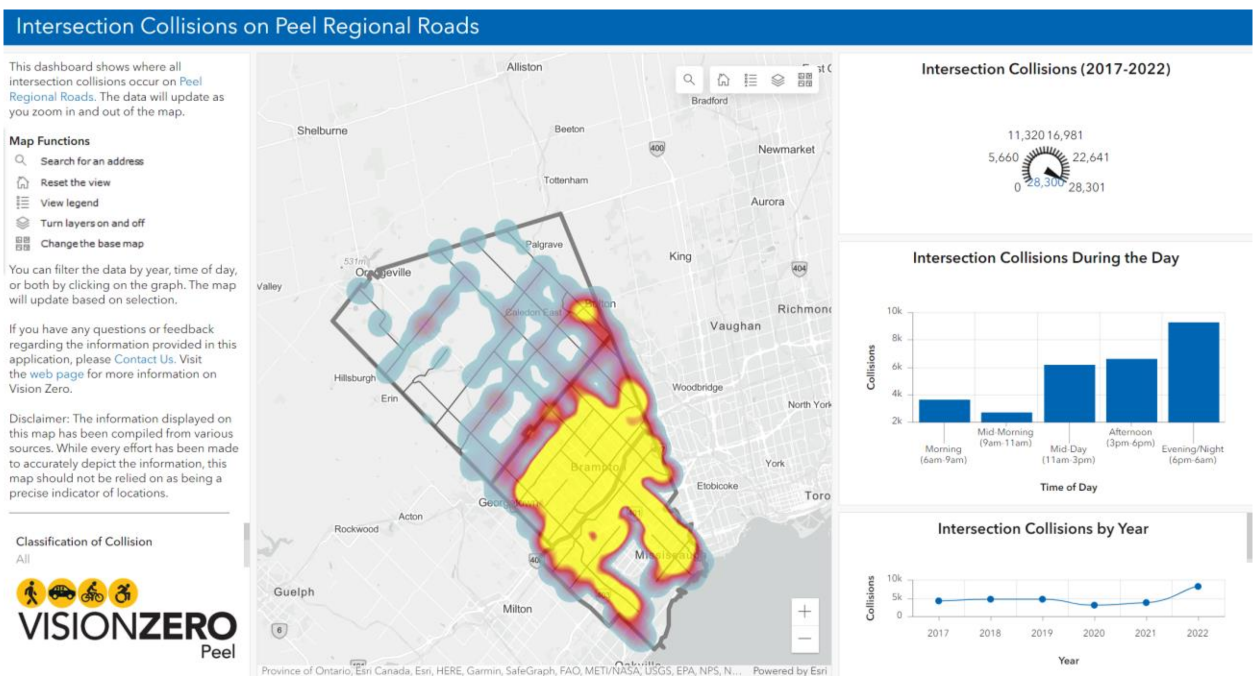



Figure 2-1 (b): Existing transportation dashboards – Intersection collisions on Peel Regional Roads

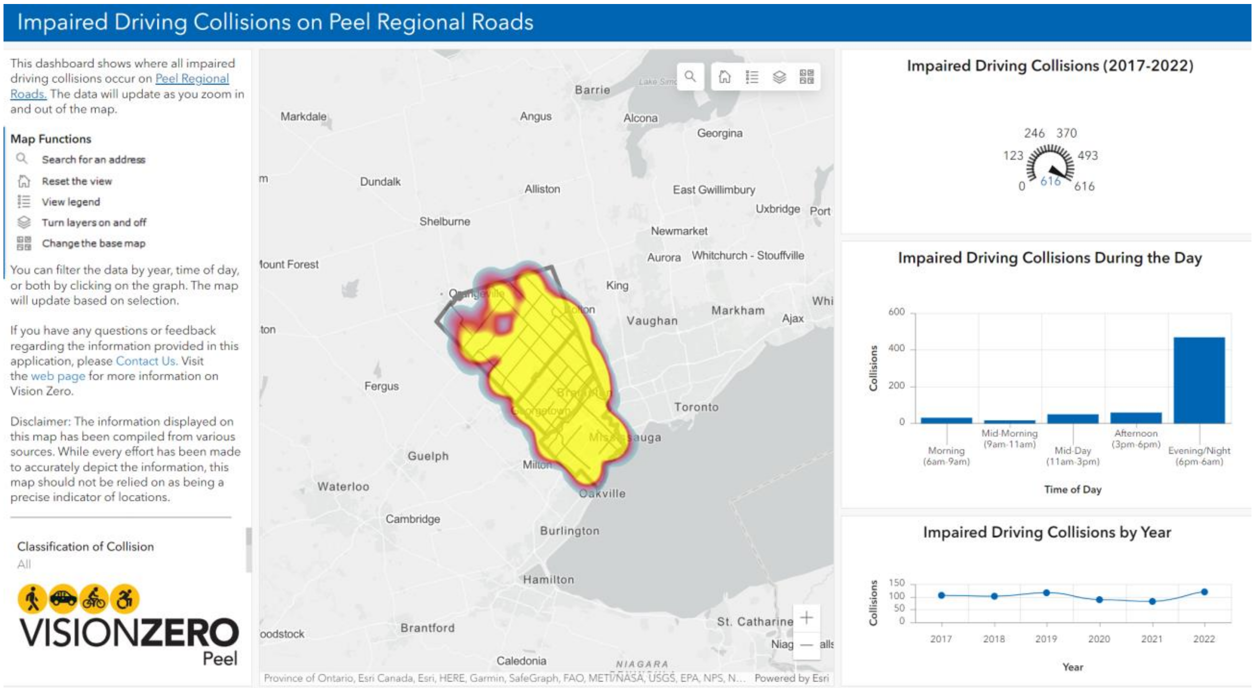



Figure 2-1 (c): Existing transportation dashboards – Impaired driving collisions on Peel Regional Roads

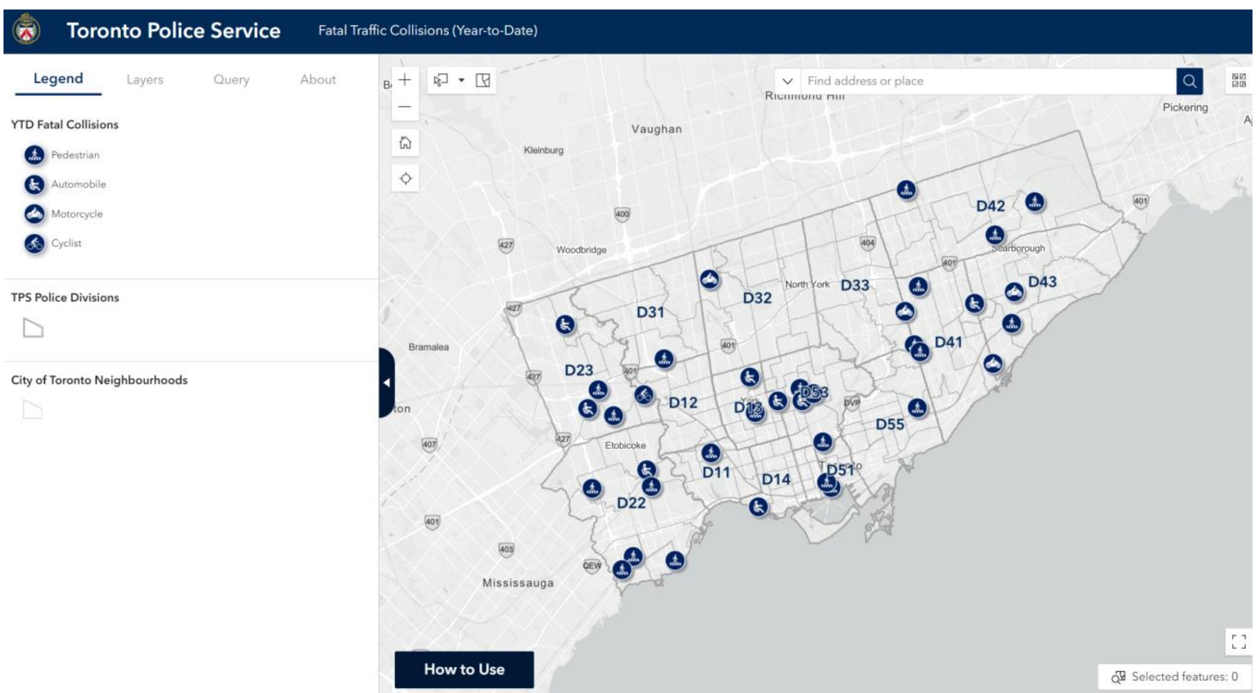



Figure 2-1 (d): Existing transportation dashboards – Fatal traffic collisions

## 2.6 Generics of ArcGIS Pro

ArcGIS Pro is one of the visualization platforms used by transportation engineers and analysts to visually illustrate a complex transportation problem (Motamed, 2022). ArcGIS Pro has been used to visually illustrate the path followed by trucks to reach their destination (Asborno et al., 2021). It has also been used to depict intra-city freight transportation and map demand delivery estimation using delivery stop counts obtained from GPS data (Moore, 2019). In addition, ArcGIS Pro has been deployed to model multiple routing cases for freight transportation. A significant advantage of ArcGIS Pro is its capability to accurately measure distances (Lyu et al., 2021). ArcGIS Pro has an inbuilt database of roads and historic traffic information which supplements the analysis for travel time and route selection.

ArcGIS Pro provides advanced analytics tools that can be used for visualizing data and performing analysis pertaining to forecasting, clustering, and regression. The software allows users to perform complex data analysis and identify insights from the dataset. ArcGIS Pro can be integrated with ArcGIS Online and Python and can perform 2D and 3D analysis. ArcGIS Pro provides functionalities to automate processes and workflows within any dashboard. ArcGIS Pro has provisions for generating geoprocessing models and scripts to automate repetitive tasks. This automation improves efficiency and enables the user to create powerful and visually compelling dashboards. *Appendix I – ArcGIS Pro Algorithm Model* shows the Workflow created for linking collision and mobility data for Region of Peel.

As noted in prior research, visualization in ArcGIS Pro needs to consider certain issues. Firstly, the quality of data must be controlled. Any data that is not consistent or lies outside a specified threshold should be discarded. This is essential to avoid bias in data visualization (Asborno et al., 2021). Secondly, attempts should be made to make the model simple, transparent, and insightful (Motamed, 2022). This should help to avoid errors while mapping the data. Thirdly, the visualization of the data should be simple and easy to understand. This is important because decision makers may not be well versed in complex transportation models (Padilla et al., 2018).

ArcGIS Pro has a function that can simultaneously use location and values to measure the spatial autocorrelation between variables. Spatial autocorrelation refers to the degree to which variables at a given geographical location are correlated with the values of the same variable at nearby locations, and indicates whether similar values tend to cluster together or not. Variables include attributes such as collisions, traffic congestion, and traffic flow patterns. The attributes are spatially analyzed to identify any clustering or dispersion across a geographic area The statistical tool used is Moran's Index, also known as Moran's I. Moran's I is based on an inferential statistic, which means that the results are used to accept or reject the null hypothesis (the null hypothesis being that the elements are randomly distributed across space). The tool generates a z-score and a p-value that is used to indicate whether there is a statistically significant difference in the spatial distributions. Moran's I is bound between -1.0 and 1.0, with -1.0 indicating dispersed spatial correlation and 1.0 showing a high level of spatial clustering. Moran's I has been used to model Carbon Emission Efficiency (CEE) in freight transportation (Zhao et al., 2022). It has also been used to examine the relationship between economic growth and the transportation sector in a study that focused on the spatial correlation between rail and road freight volumes (Boldizsár et al., 2023).

The available literature suggests that Moran's Index can be used to study the spatial distribution of traffic congestion, collisions, or traffic flow patterns.

## 2.7 Limitations in Literature and Potential for New Research

The literature review showed a number of limitations in existing research. In particular, all the studies evaluated freight fluidity on freeways. There is limited research focused on freight fluidity on arterial roads, especially in a municipality of the scale of the Region of Peel. Evaluating freight fluidity for arterial roads on an entire road network poses its own set of challenges in the form of the millions of rows of dataset which needs to be collated and processed (Cedillo-Campos et al., 2019).

There is a gap in prior research that investigates the spatial distribution of collisions or freight fluidity measures for trucks. Moran's I is used to find the relationship between a single variable (such as collisions) and its surrounding values, but no research has estimated Moran's I for truck collisions or freight fluidity measures.

An advantage of Moran's I is its ability to find the spatial autocorrelation for a single variable such as collisions (Krisztin, 2017). Moran's I is not used to investigate the correlation between two variables, but there is an opportunity to identify whether there is any clustering of collisions or freight fluidity measures by spatial location.

Several statistical techniques, such as Pearson's Correlation and Kendall's Rank Correlation, are used to investigate the strength and direction of association between two sets of data. Prior research has attempted to find the correlation between mobility and collisions for all transportation modes (Fitzpatrick et al., 2018). There is a gap in research that primarily focuses on freight movement. Previous research is limited to vehicle miles travelled (VMT), which was used as the sole mobility measure (Fitzpatrick et al., 2018), and the study's results found no conclusive evidence of a statistical correlation between collisions and mobility (Fitzpatrick et al., 2018). There is an opportunity to focus on freight transportation, investigate the possibility of a correlation between truck collisions and mobility, and help to fill this gap in the literature.

Freight transportation in Canada lacks an operational freight fluidity framework that considers the entire supply chain. Freight in Canada is currently examined through a macroscopic lens that analyzes the movement of goods based on commodity, geography and mode (Government of Canada, Statistics Canada, 2018). The visualization of freight fluidity measures is complex owing to the layers of temporal and spatial variations, but a dashboard showing the application of freight fluidity in a municipality in Canada can be a step forward in presenting the relevant data and the study can help evaluate freight resilience in Canada. Future studies could then refine and expand the concepts explored across the entire province and further to achieve the objective of ‘fluid’ freight movements across Canada.

# CHAPTER 3: STUDY AREA, DATA AND DASHBOARD

This chapter considers the scope of research with information pertaining to study area and the data used for this research. The chapter also discusses the features of the freight fluidity dashboard, developed as a tangible outcome of this research.

## 3.1 Study Area

The study area for this research was the Region of Peel. The Region of Peel is a regional municipality in the Greater Toronto Area (GTA) in Southern Ontario. It consists of three municipalities: the City of Mississauga, the City of Brampton and the Town of Caledon.

Figure 3-1 shows the geographical location of these municipalities in the Region of Peel.

The Region of Peel has a land area of 1,254 square kilometers and a population of around 1.45 million, with 1 in 10 Ontarians now living in this Region (Census, 2016). Statistics Canada records a gradual but steady expansion of the Region of Peel's permanent population. The population grew at an average rate of 1 percent per year between 2016 and 2021 and is forecast to reach 2.28 million by 2051 (2021 Performance and Outlook, 2021). The influx of population in the Region will further stress the existing road infrastructure, leading to congestion and delays. The anticipated surge in population is likely to contribute to increased vehicular traffic, potentially leading to additional stress on transportation networks. As the Region of Peel evolves into a vibrant and populous urban center, it becomes imperative to proactively address the challenges associated with the expanding population to ensure the continued efficiency and sustainability of the Region's transportation systems.

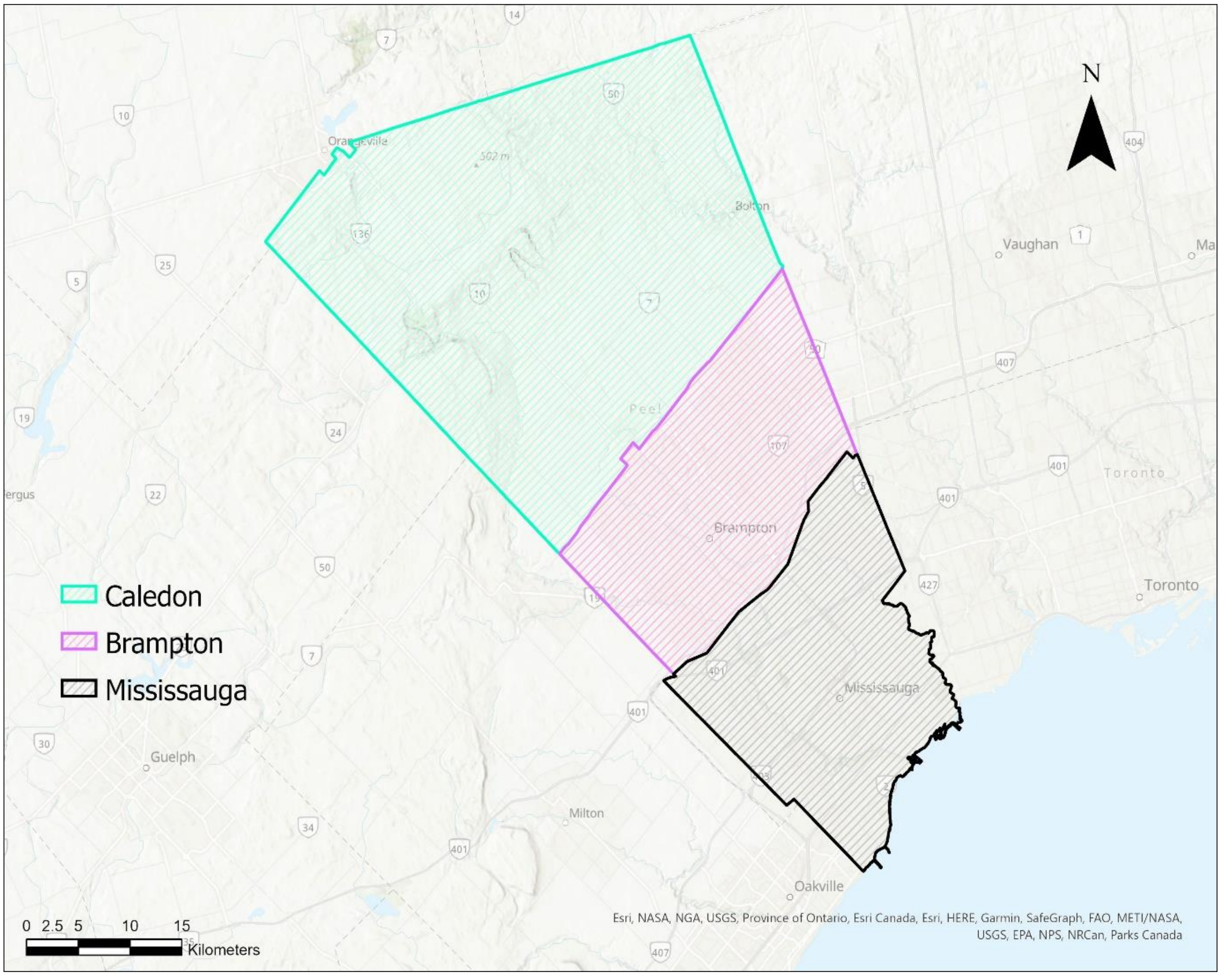



Figure 3-1: Municipalities in Region of Peel

## 3.2 Mobility Data

The mobility data used in the study were obtained through the Freight Data Warehouse (FDW). The FDW was founded in 2021 and is a part of the Smart Freight Centre established by the collaboration between Region of Peel, McMaster University, the University of Toronto, and York University (Smart Freight Centre, 2023). The FDW uses HERE data to estimate travel speeds by time of day by road segment. HERE data were found to be the best choice for obtaining freight fluidity data for the Region of Peel. HERE data work better than GPS and Bluetooth detection techniques for oversaturated conditions on arterial roads (Kondyli et al., 2018). Although HERE data cannot be 100 percent accurate in all traffic conditions, the data are considered to be one of the better data source for estimating travel time compared to other data sources such as Waze and Tom Tom Traffic (Verendel and Yeh, 2019).

The Freight Data Warehouse (FDW) is a web portal that consolidates, manages, and distributes freight data in a secure on-line environment (Freight Data Warehouse, 2023). Data obtained from the FDW were used to gather information about truck movements in the Region of Peel during 2019 and 2020. Hourly speed data for trucks were extracted from the FDW portal for all arterial road segments in the Region of Peel, covering the period from January 1, 2019, to December 31, 2020. This hourly data allows a more detailed nuanced analysis of traffic patterns, offering better insights into peak hour congestions and dynamic fluctuations of traffic throughout the day. On the other hand, Annual Average Daily Traffic (AADT) data provides a high-level, less detailed overview, which makes hourly data more valuable for this type of analysis.

Figure 3-2 shows the parameters used for extracting data from the FDW platform. Some of the major parameters included mode (trucks), functional class of road (arterial road), data intervals (1 hour) and date range (1$^{st}$ January 2019 to 31$^{st}$ December 2020). The extracted data obtained were used to calculate the freight fluidity measures. *Appendix II – Steps to extract data from Freight Data Warehouse* provides a detailed step-by-step process showing how the data were obtained from the FDW platform.

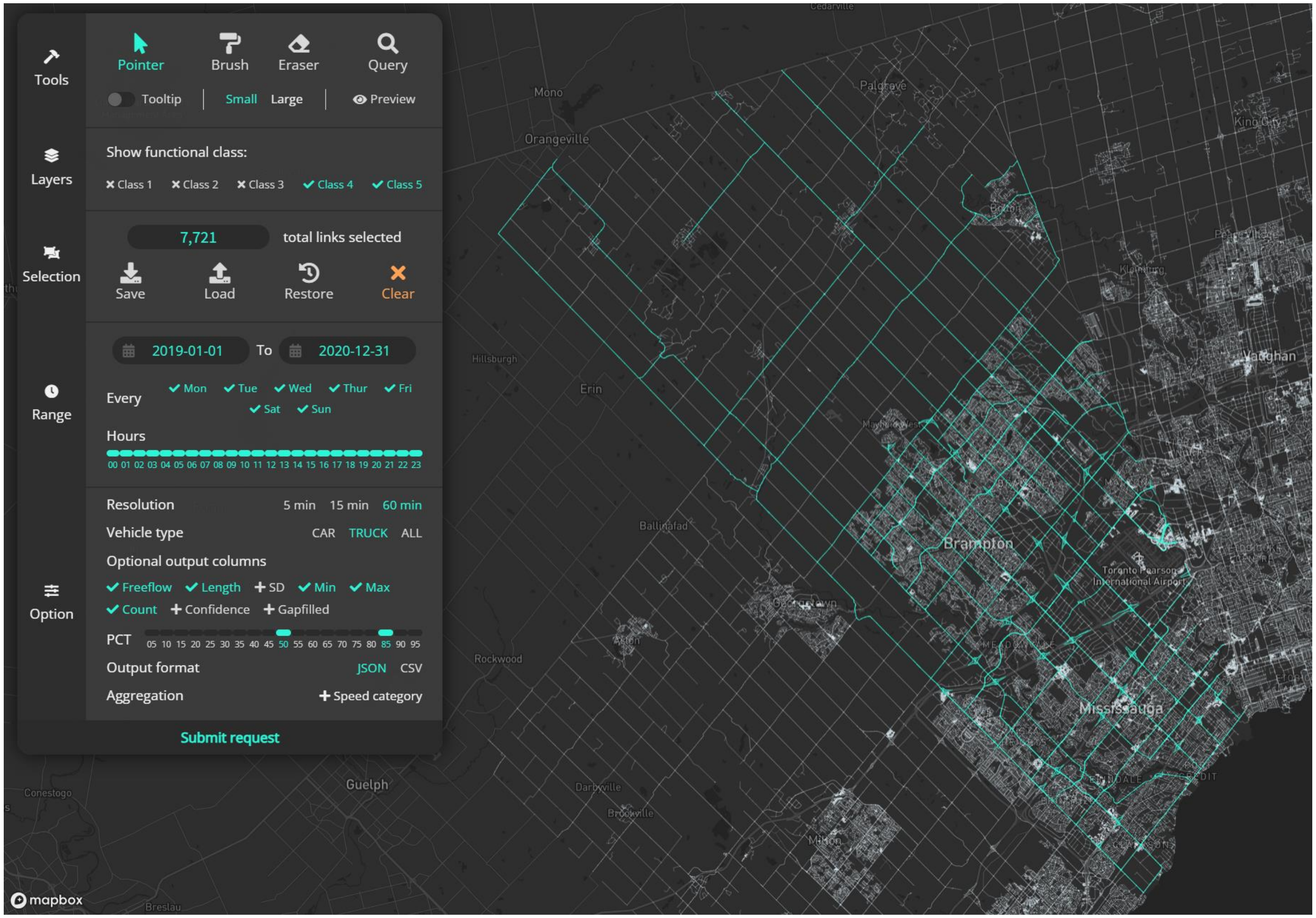



Figure 3-2: Parameters for extracting data for Region of Peel from Freight Data Warehouse

The raw data obtained from FDW consisted of 11,276 Comma Separated Values (CSV) files with hourly data for each road segment in a separate file. The CSV is the most commonly used format for importing and exporting data for spreadsheets and Python databases (Python documentation, 2023). The CSV files consist of plain text data separated by commas, making them compatible with software applications such as MS Excel and Python (Wade, 2020). The total size of the dataset was 197,667,360 rows x 11 columns which was beyond the capacity of MS Excel to handle. The data were crude and required processing and cleaning. Python software was used for data massaging and processing. The data were transformed into an encoded data format that could be parsed by Python. Algorithms were developed in Python for data cleaning and quality assurance.

*Appendix III – Python code snippets* shows the Python script developed for processing Region of Peel data.

The tasks involved in the study's data processing are discussed below:

1. **Import data:** Initially, the data were stored as a separate CSV file for each road segment. The first step involved importing the data into Python using 'pandas' and 'numpy' libraries. These are some of the most commonly used Python libraries that facilitate fast and efficient numerical computation of large datasets.

2. **Remove duplicates:** The data were checked for any duplicate values to avoid skewing in the results. No duplicates were found in the dataset.

3. **Detect Outliers:** Outliers refer to extreme values that are significantly different from other values, possibly due to faulty data collection. Outliers were defined as a speed

that exceeded 120 km/h. Arterial roads in Region of Peel typically have a posted speed limit in the range of 60 km/h to 90 km/h (Road network in Peel Region, 2011). It is estimated that more than 77 percent of trucks in Canada and the United States have speed limiters which restrict truck speeds in the range of 100 km/h to 112 km/h (Transport Canada, 2013). A buffer of 8 km/h was used to avoid removal of genuine data. Only 0.047 percent of the hourly speed data collected for all segments across the Region of Peel from 1$^{st}$ January 2019 to 31$^{st}$ December 2020 exceeded 120 km/h. These data points were removed from the dataset.

4. **Check negative and null values:** Negative and zero values for speed were checked, as they could distort the analysis. No negative or null speeds were observed in the dataset.

5. **Sense check:** The mean speed was checked against the free flow speed to obtain a broad indication of truck speeds on arterial roads in the Region of Peel. The free flow speed provided by HERE Technologies represents the speed at which traffic flows when it is not slowed by congestion. It was observed that around 12 percent of mean speeds were higher than free flow speeds, which is in line with what was expected. On certain roads and at certain times of the day when traffic volumes are low and there is no congestion, drivers tend to drive faster than the free flow speeds.

6. **Data type conversions:** The dataset consisted of speed buckets in multiples of 5 km/h. The speed data were converted into travel time using the following equation:

   *Travel Time = Length of road segment / Speed* [Equation 9]

The speed data by segment obtained from the FDW were used to calculate freight fluidity measures (TTI, PTI, and BI).

### 3.3 Collision Data

The collision data were obtained specifically for trucks travelling in the Region of Peel. The source of the data was the Region of Peel's 'OpenData' portal available via https://data.peelregion.ca website (Data Portal - Region of Peel, 2022). The 'OpenData' portal is a central hub for accessing transportation data for the Region of Peel and is available to the public under an open license. The collision data were obtained from 2018 to 2020 to analyze and compare the truck movements before the pandemic and during the pandemic. The data were available in the form of a CSV file that contained all roads in the Region of Peel. The roads were classified by road class.

Collisions that occurred on arterial roads were identified. The arterial truck collisions were classified into the following four categories according to the extent of damage caused:

1. **Fatal injury:** A collision that results in the death of an individual. It refers to any person inside or outside a vehicle that died due to a collision, either immediately or after a period of time (Federal Highway Administration, 2022).
2. **Non-fatal injury:** A collision that causes physical harm or damage to the body that is not severe enough to cause the person's death but still instills pain, minor injury or loss of function (Federal Highway Administration, 2022).
3. **Property damage only (PDO):** A collision that does not lead to any injury or loss of life but causes damage to the vehicle or property involved in the collision (Federal Highway Administration, 2022).

4. **Non-Reportable:** A collision that does not lead to any injury or any significant loss of property. It includes minor dents or scratches that might occur to vehicles involved in a minor collision and is not worth reporting to any higher authorities (Federal Highway Administration, 2022).

The collision data were obtained from Permanent Count Stations (PCS) installed at strategic locations across the Region of Peel. The stations are installed with sensors (in this case Houston SpeedLane Pro radars) that automatically record and collect data pertaining to vehicle class, location and road conditions. PCS stations use dual beam speed trap technology that provides accurate measurements without the need for calibration (Houston Radar, 2022).

A sense check was conducted on the data to identify the specific locations or stretches of road where truck collisions were most common. It was observed that almost half of all truck collisions in the Region of Peel took place in Brampton. The observation concurs with a Peel Regional Police (PRP) report which estimated that Brampton accounted for almost half of collision fatalities or life altering injuries in the Region of Peel (Peel Regional Police, 2022). Brampton is beset with industrial buildings and warehouses with large tracts of land zoned for industrial use. It employs more than 50 percent of the transportation and warehousing labour force in the Region of Peel (InSauga Digital Media, 2016). Brampton's proximity to Pearson Airport and access to Highway 401 makes it a favoured destination for freight transportation, leading to an increased number of truck collisions.

The collision data also closely matched the Region of Peel's interactive dashboard on impaired driving (Region of Peel, 2022). The dashboard for impaired driving consists of all modes of transportation and is not specific for trucks. A visual inspection of the dashboard for impaired driving revealed that the highest number of impaired driving crashes was observed in Brampton, followed by Mississauga and Caledon (Karen Longwell, 2022). The collisions data obtained for trucks showed a similar pattern with the highest number of collisions observed in Brampton followed by Mississauga and Caledon.

Table 3-1 shows Region of Peel truck collisions by location and type of collision for 2018, 2019 and 2020.

Table 3-1: Geolocations of truck collisions in Region of Peel

| **Collision Type** | **Municipality** | **Caledon** | **Brampton** | **Mississauga** | **Total** |
|---|---|---|---|---|---|
| Fatal collision | 2018 | 0 | 2 | 0 | **2** |
| | 2019 | 2 | 0 | 0 | **2** |
| | 2020 | 0 | 1 | 2 | **3** |
| Non-fatal collision | 2018 | 5 | 20 | 14 | **39** |
| | 2019 | 7 | 23 | 17 | **47** |
| | 2020 | 9 | 20 | 5 | **34** |
| Property Damage Only | 2018 | 48 | 223 | 211 | **482** |
| | 2019 | 42 | 210 | 214 | **466** |
| | 2020 | 54 | 148 | 138 | **340** |
| Non-reportable | 2018 | 0 | 3 | 5 | **8** |
| | 2019 | 0 | 4 | 6 | **10** |
| | 2020 | 1 | 6 | 2 | **9** |
| Total | 2018 | 53 | 248 | 229 | **530** |
| | 2019 | 51 | 237 | 237 | **525** |
| | 2020 | 64 | 175 | 147 | **386** |
| **Grand Sum** | **2018 + 2019 + 2020** | **168** | **665** | **613** | **1446** |

## 3.4 Dashboard

Dashboards have gained prominence in various domains including transportation, healthcare, and business analytics. Dashboards facilitate the visual depiction and analysis of datasets in a manner that is easy to comprehend. The field of transportation generally involves large complex datasets with millions of rows of data that cannot be displayed using conventional data analysis tools such as MS Excel. In such cases, dashboards provide a platform for displaying data in a clear and concise manner. The data in a dashboard is generally crosslinked with functionalities that allow filtering, sorting and focusing on what is needed. Using a dashboard, transport analysts and planners can easily identify trends, patterns, and outliers that otherwise may not be that apparent in the raw data, and decision makers can make decisions in a fast and efficient manner. Dashboards also enable transparency in data sharing as the complex data set can be shown to the public in a dynamic visual platform.

The use of traffic data to create dashboards can be pivotal in evaluating freight fluidity performance measures and reducing delays and congestion across the road network. A centralized dashboard that can track the entire road network using data analytics can help improve the efficiency of freight transportation (UC Berkeley, 2019). A traffic bandwidth showing frequent high congestion levels on a particular roadway can help decision makers identify underlying causes, such as increased traffic or inefficiencies in road design. The historical traffic data illustrated in a dashboard can also be used for demand forecasting. The logistics companies can schedule resources and adjust routes to account for the expected congestion, thereby saving time and money.

Figure 3-3 shows the process for visualizing and analyzing collision and freight fluidity measures data using a dashboard.

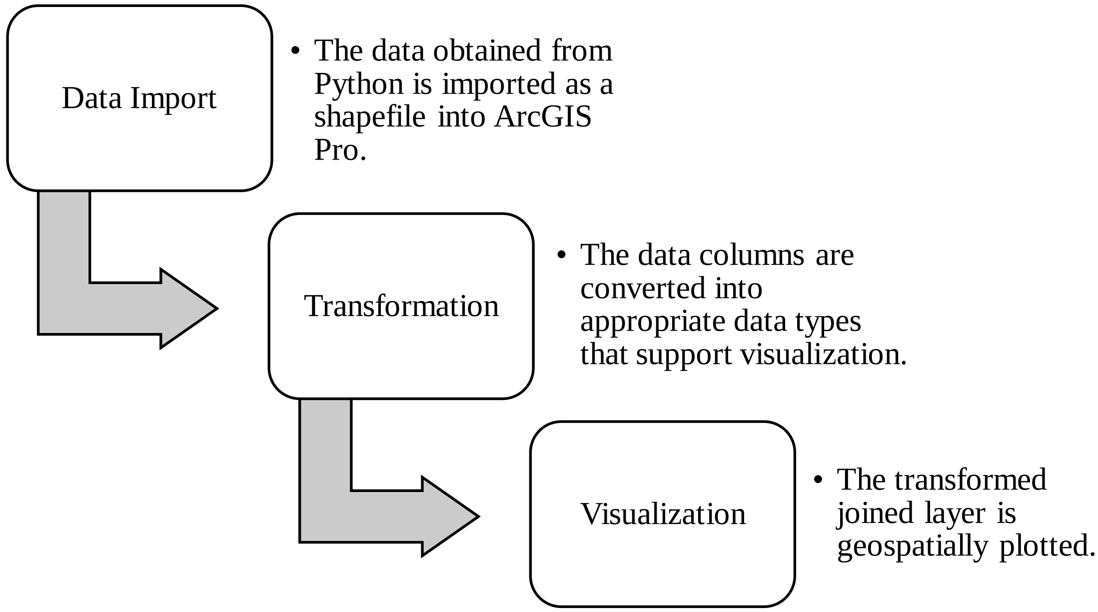



Figure 3-3: Steps for extracting visualizing data in ArcGIS Pro

A freight fluidity dashboard is a tangible product created as part of this research. The dashboard is specific for Region of Peel and incorporates freight fluidity and collisions data for 2019 and 2020. The dashboard provides a one-stop-shop for decision makers to visually analyze the freight fluidity measures (TTI, PTI and BI) and collisions across Peel Region, and can help decision makers to take decisions more proactively.

The dashboard allows users to select any date range between 1$^{st}$ January 2019 and 31$^{st}$ December 2020. This gives the user the flexibility to analyze different durations on the same platform. The platform includes all arterial roads in Peel Region and allows a user to select and study any arterial(s). The user can also evaluate freight fluidity and/or collision measures for each municipality (Mississauga, Brampton and Caledon) or for the whole Region. The dashboard can show temporal variations (hourly, weekly, monthly, and yearly) at the click of a button. Another useful feature for spatial analysis is the functionality automatically updates information as the user zooms in/out of the map.

The dashboard is designed primarily to serve the following purposes:

1. **Monitoring Performance:** This user-friendly tool enables decision makers to monitor freight movement efficiency, assessing the transportation network's performance over any specified date range from January 1, 2019 to December 31, 2020. Hourly data analysis offers a detailed examination of the freight transportation operations throughout the day.
2. **Identifying Congestion Locations:** By analyzing hourly data, especially during AM and PM peak periods, the dashboard aids in identifying congestion and bottlenecks within the freight transportation network. This information is crucial for addressing infrastructure limitations and improving traffic flow during peak hours.
3. **Enhancing Safety:** Integrating collision data, the dashboard sheds lights on safety concerns in freight transportation. Analyzing collision data by specific times and impact configurations enables targeted safety improvements, potentially reducing collisions and enhancing road safety for both freight vehicles and other roadway users.
4. **Optimizing Scheduling and Routes:** Logistics operators can use the dashboard to optimize freight scheduling and route planning. Understanding traffic patterns and congestion locations helps in selecting the most efficient routes, thus improving supply chain efficiency.

5. **Informing Policy and Planning Decisions:** Decision makers, especially in the Region of Peel, can leverage the dashboard to make informed decisions about infrastructure investments and policy changes. Analysis of freight fluidity and collision data provides valuable insights for strategies to enhance the freight transportation system's mobility and safety.

This dashboard helps monitor freight performance in the Region of Peel by identifying bottlenecks, enhancing safety, optimizing scheduling and routes, and informing policy and planning decisions.

Figure 3-4 provides a view of the functionalities of the freight fluidity dashboard.

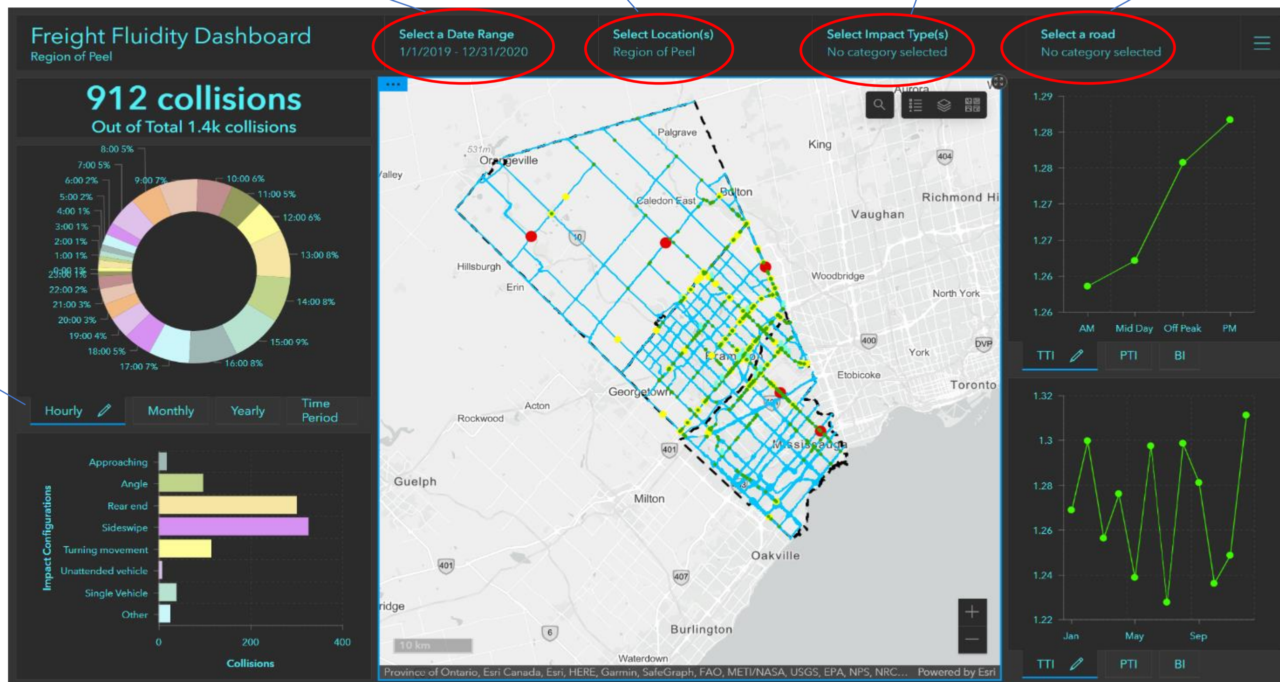
1. Select a Date Range between 1st January 2019 to 31st December 2020.

2. Select Location(s) – Mississauga, Brampton and/or Caledon.

3. Select Impact Type(s) – pertaining to collision.

4. Select any particular road(s) of interest.

User can change the temporal values – Hourly, Monthly, Yearly or Time Period




User can change and analyse the freight fluidity measures – TTI, PTI or BI

Zooming In/Out of the map will automatically update information for that extent.

Figure 3-4: Functionalities of the freight fluidity dashboard

The freight fluidity dashboard provides a practical platform for decision makers and freight logistics firms to make more informed decisions in an effective and efficient manner. The outputs obtained from the dashboard include:

1. **Collisions by Location:** The dashboard dynamically identifies the spatial distribution of collisions, automatically updating numbers as users zoom in or out of the map. This feature helps pinpoint collision hotspots and analyze their geographical patterns.
2. **Variation by Municipality:** The dashboard is equipped to analyze collisions and freight fluidity measures on a municipality level, encompassing Caledon, Brampton, and Mississauga. Users have the flexibility to examine data either for a specific municipality or any combination of municipalities collectively. The interface allows seamless selection, with automatic updates reflecting the chosen municipality or municipalities.
3. **Specific Road Selection:** Users can select specific arterial roads for focused study on freight fluidity and collisions, enabling detailed analysis for the chosen road segments. This targeted approach facilitates a detailed analysis of transportation dynamics on specific routes.
4. **Impact Categorization:** The dashboard categorizes each collision based on impact type and configuration, aiding in understanding the severity of collisions in different regions and the specific configurations contributing to these collisions.
5. **Freight Fluidity Measures:** The dashboard has the capability to provide freight fluidity measures, allowing users to analyze either individual road segments or the entire Region of Peel collectively. This functionality is invaluable for identifying mobility challenges, congestion issues, and optimizing the overall efficiency of freight transportation.

6. **Temporal Variations:** The dashboard provides temporal insights by offering freight fluidity measures and collision data based on various time periods throughout the entire 24-hour day. Additionally, it facilitates a macroscopic analysis, allowing users to examine trends and variations over weeks, months, or the entire year. This temporal granularity aids in understanding the cyclical patterns and planning for peak periods.

This dashboard provides a multifaceted analysis incorporating collisions and freight fluidity measures by location and time periods. It delves into impact categorization and temporal variations. The dynamic features presented in the dashboard provide a nuanced understanding of freight transportation system in the Region of Peel, offering valuable insights for decision-makers and transportation professionals.

# CHAPTER 4: ANALYSIS OF RESULTS

The chapter considers the descriptive data analysis for collisions and freight fluidity measures. Spatial relationship and correlation between collisions and freight fluidity measures are also considered in this chapter. A variety of statistical tools and visualization techniques were used to present the findings.

## 4.1 Descriptive Data Analysis

Descriptive data analysis refers to using simple statistical tools to gain insights into the characteristics of data. Descriptive data analysis of transportation data can be used to provide insights that can then be used to identify travel patterns and inform decision-making (Kothapalli, 2014). The data analyzed in this research includes parameters pertaining to collisions and mobility. Both spatial and temporal analyses were conducted on the study's collision and mobility data.

Spatial analysis focuses on representing transportation data in relation to its geographic location or spatial distribution. This research involved representing collisions and freight fluidity data geospatially across the Region of Peel. GIS maps were created to analyze the spatial distribution of transportation data. Elements such as road networks, intersections and traffic flow were mapped to understand the geographic patterns of traffic flow, congestion, and safety (Miller, 2010).

Temporal analysis refers to the time-dependent analysis of data. It focuses on examining patterns and trends over a period of time. Aspects of temporal analysis include daily, weekly, or monthly variations in travel times, volumes, or collisions. Urban areas, in particular, experience noticeable temporal variations which reflect differences in travel demand based on time (Kim, Park and Sang, 2008). This research conducted temporal analyses to establish time-dependent variations (if any) for freight fluidity measures and truck collisions in the Region of Peel. The analysis was designed to help identify congestion patterns, weekly variations, seasonal trends, and long-term trends.

Conducting an analysis at a more disaggregated level can help identify anomalies and allow for useful comparisons (Huber and Lißner, 2019). In this study, a multi-step disaggregation approach was undertaken. The data were first analyzed for the entire Region of Peel, then disaggregated by municipality (Mississauga, Brampton and Caledon), and then to the ward level. Disaggregation of data can help improve the accuracy of analysis by enhancing the understanding of a region's characteristics, providing analytical insights into different areas, and identifying any patterns or trends specific to a region. Disaggregation also helps to identify whether the characteristics of a particular location are responsible for skewing the overall results (Park and Goldberg, 2021).

This chapter aims to identify patterns, trends, and key insights from the data, which can help identify locations prone to truck collisions and congestion in the Region of Peel. One of the most important prerequisites for a descriptive data analysis is to ensure that the data are processed, as discussed in Section 3.2, before being used for analysis (Vlahogianni and Karlaftis, 2011). Summary statistics of the collision and freight fluidity data were determined and are presented in the following sections. Summary statistics refer to information that gives a brief and simple description of the data using measures such as the mean, median, minimum, and maximum values for each relevant parameter. The summarized outcomes provided a concise and easy to understand overview of truck collisions and freight fluidity data that can be used for informed decision-making, policy development, infrastructure planning, and resource allocation.

## 4.2 Collision Data Analysis

This sub-section focuses on analyzing truck collisions that occurred in the Region of Peel between 2018 and 2020. Temporal and spatial analyses were conducted, and summary statistics are presented. Figure 4-1 shows the yearly breakdown of truck collisions between 2018 and 2020. The yearly comparison was conducted to help identify the effect of the pandemic on collisions.

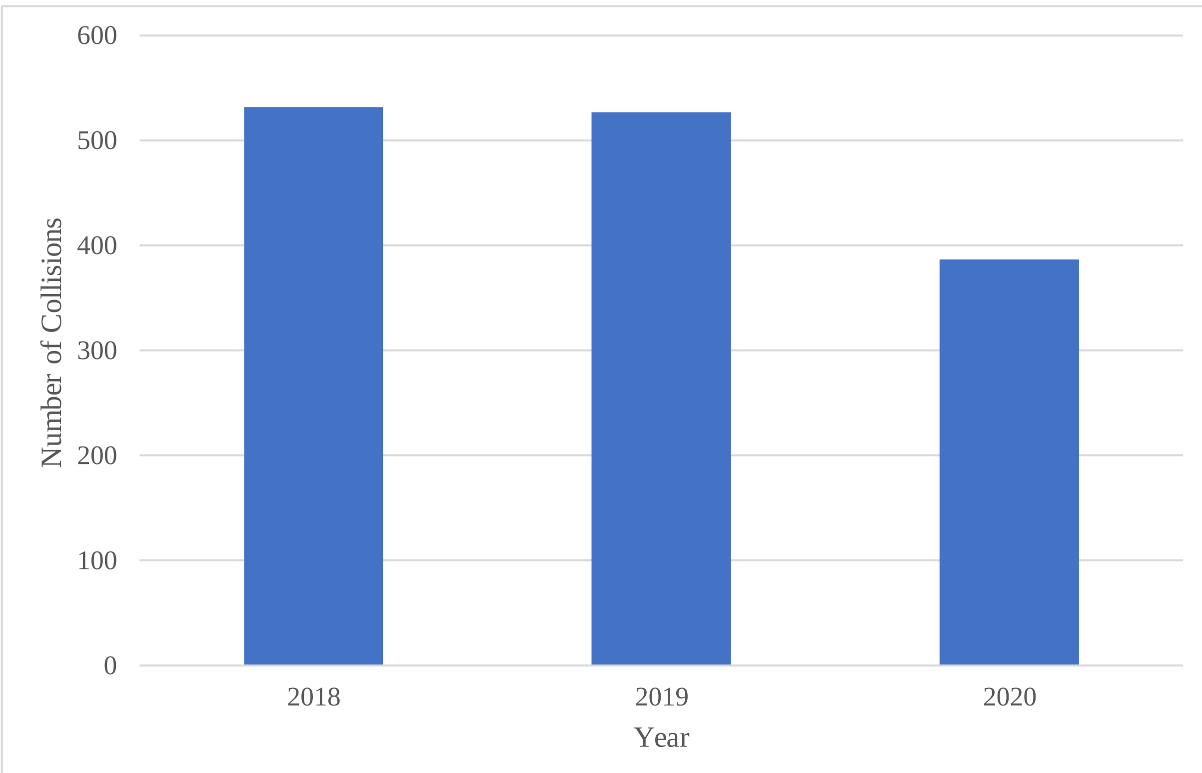



Figure 4-1: Total truck collisions by year in the Region of Peel

The number of collisions was similar in 2018 and 2019 (two consecutive non-pandemic years). The total number of truck collisions in 2018 was 532 compared to 527 in 2019. This is a less than one percent reduction in collisions after implementation of the ‘Vision Zero Road Safety Strategic Plan’ by the Region of Peel in September 2018 (Vision Zero, 2018). However, a substantial decrease in truck collisions was observed from 2019 to 2020: truck collisions dropped from 527 in 2019 to 387 in 2020, a 27 percent reduction. This drop can be attributed to the lockdown and reduction of road traffic during the pandemic. Truck traffic in urban areas across the Peel Region showed a marked decrease (-7.8 percent) with the Covid-19 lockdown in 2020. The 2-way cross border truck flow between USA and Canada declined from 10.9 million trips in 2019 to 10.1 million trips in 2020, an 8.7 percent decrease in cross border truck movement when compared with the 3-year average (Transportation in Canada 2020 - Overview Report, 2021). The decline in truck traffic is likely to have contributed to the substantial decrease in collisions observed in 2020.

Figure 4-2 shows the geolocations and level of severity of truck collisions on arterial roads in the Region of Peel from 2018 to 2020. The collisions were plotted in ArcGIS Pro to better visualize sites prone to collisions.

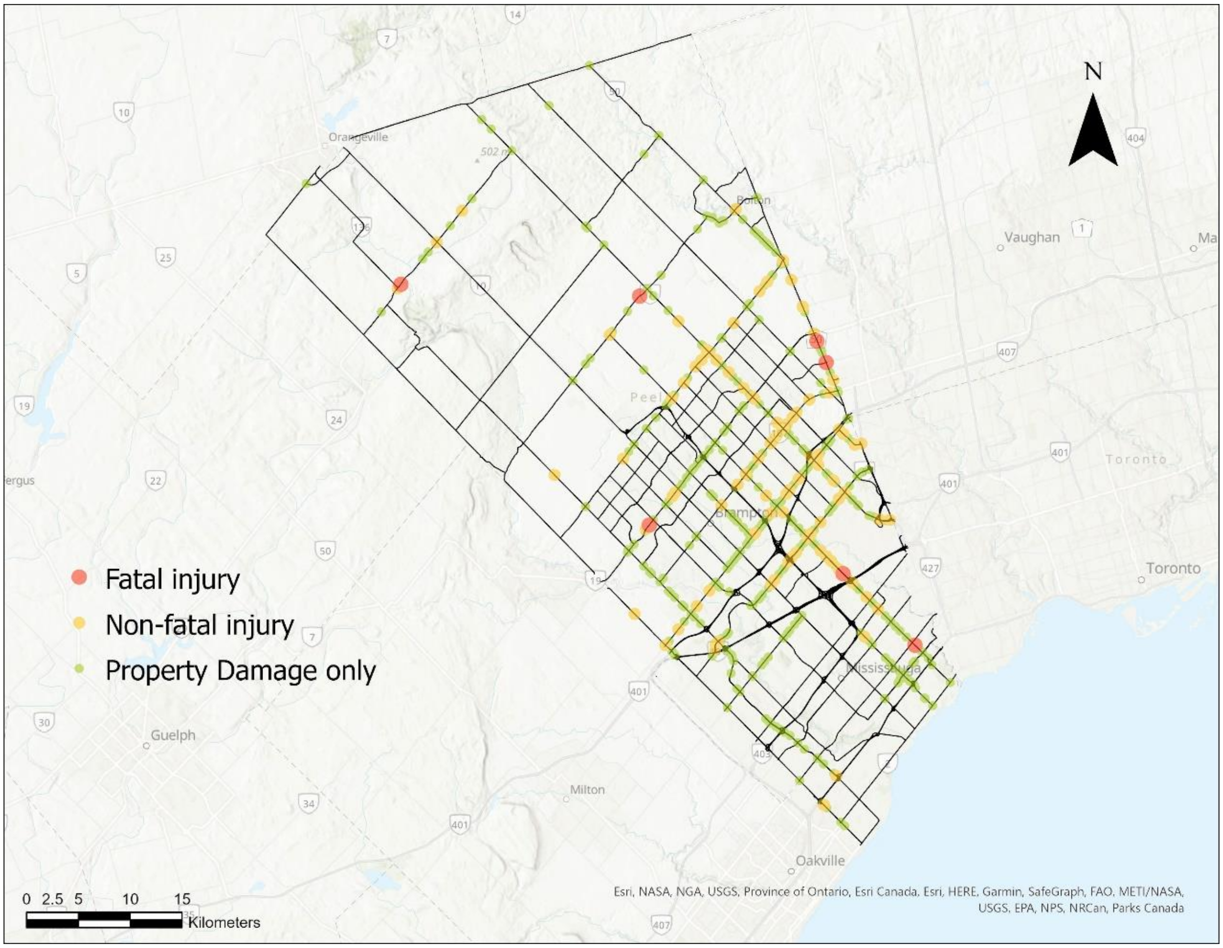



Figure 4-2: Geolocations of truck collisions in Region of Peel

It is evident from Figure 4-2 that the majority of truck collisions are concentrated in the municipalities of Brampton and Mississauga. Table 4-1 shows the collision distribution based on municipality.

Table 4-1: Collision distribution for trucks based on Municipality

| Municipality | Collisions | | | | | Arterial Road Network (km) |
|---|---|---|---|---|---|---|
| | Year | | | Total | Average over 3 years | |
| | 2018 | 2019 | 2020 | | | |
| Caledon | 53 | 51 | 64 | 168 | 56 | 334 |
| Brampton | 248 | 237 | 175 | 660 | 220 | 266 |
| Mississauga | 229 | 237 | 147 | 613 | 204 | 212 |
| **Total** | **532** | **527** | **387** | **1446** | **482** | **812** |

Table 4-1 shows that the number of truck collisions on arterial roads does not necessarily depend on road length. Brampton and Mississauga accounted for 46 percent and 43 percent of total collisions respectively despite having a shorter road length compared to Caledon. This is not unexpected as a number of other factors such as condition of vehicle, driver behaviour and freight fluidity measures all contribute to collision occurrence (Kilpeläinen and Summala, 2007). This research attempts to analyze collisions by considering the relationship (if any) between collisions and freight fluidity measures. External factors such as vehicle condition and driver behaviour were beyond the scope of this research.

Truck collisions were investigated in relation to the hour of day. Factors such as traffic volume, density, and delay change over the course of a day and affect the likelihood of a collision. Table 4-2 shows the hourly collision distribution observed in the Region of Peel from 2018 to 2020. Figure 4-3 provides a bar graph of the same data to illustrate any significant variations in collision frequency during different hours. The entire 24-hour time window was selected for the analysis as the typical morning and evening peak hours may not be applicable for truck collisions (Hunt and Stefan, 2007).

Table 4-2: Hourly collision distribution for trucks in Region of Peel

| **Hours** | **Year** | | | **Total Collisions** | **Average Collisions over 3 years** |
|---|---|---|---|---|---|
| | **2018** | **2019** | **2020** | | |
| 12 AM to 1 AM | 1 | 3 | 6 | 10 | 3 |
| 1 AM to 2 AM | 5 | 8 | 5 | 18 | 6 |
| 2 AM to 3 AM | 4 | 4 | 2 | 10 | 3 |
| 3 AM to 4 AM | 6 | 7 | 1 | 14 | 5 |
| 4 AM to 5 AM | 7 | 8 | 1 | 16 | 5 |
| 5 AM to 6 AM | 13 | 8 | 6 | 27 | 9 |
| 6 AM to 7 AM | 22 | 6 | 3 | 31 | 10 |
| 7 AM to 8 AM | 43 | 21 | 10 | 74 | 25 |
| 8 AM to 9 AM | 35 | 24 | 15 | 74 | 25 |
| 9 AM to 10 AM | 40 | 31 | 25 | 96 | 32 |
| 10 AM to 11 AM | 27 | 33 | 26 | 86 | 29 |
| 11 AM to 12 PM | 29 | 28 | 22 | 79 | 26 |
| 12 PM to 1 PM | 29 | 30 | 24 | 83 | 28 |
| 1 PM to 2 PM | 44 | 42 | 36 | 122 | 41 |
| 2 PM to 3 PM | 49 | 42 | 23 | 114 | 38 |
| 3 PM to 4 PM | 39 | 53 | 33 | 125 | 42 |
| 4 PM to 5 PM | 43 | 37 | 38 | 118 | 39 |
| 5 PM to 6 PM | 27 | 41 | 31 | 99 | 33 |
| 6 PM to 7 PM | 17 | 30 | 23 | 70 | 23 |
| 7 PM to 8 PM | 13 | 26 | 16 | 55 | 18 |
| 8 PM to 9 PM | 10 | 17 | 13 | 40 | 13 |
| 9 PM to 10 PM | 9 | 15 | 16 | 40 | 13 |
| 10 PM to 11 PM | 17 | 8 | 8 | 33 | 11 |
| 11 PM to 12 AM | 3 | 5 | 4 | 12 | 4 |
| **Total** | **532** | **527** | **387** | **1446** | |

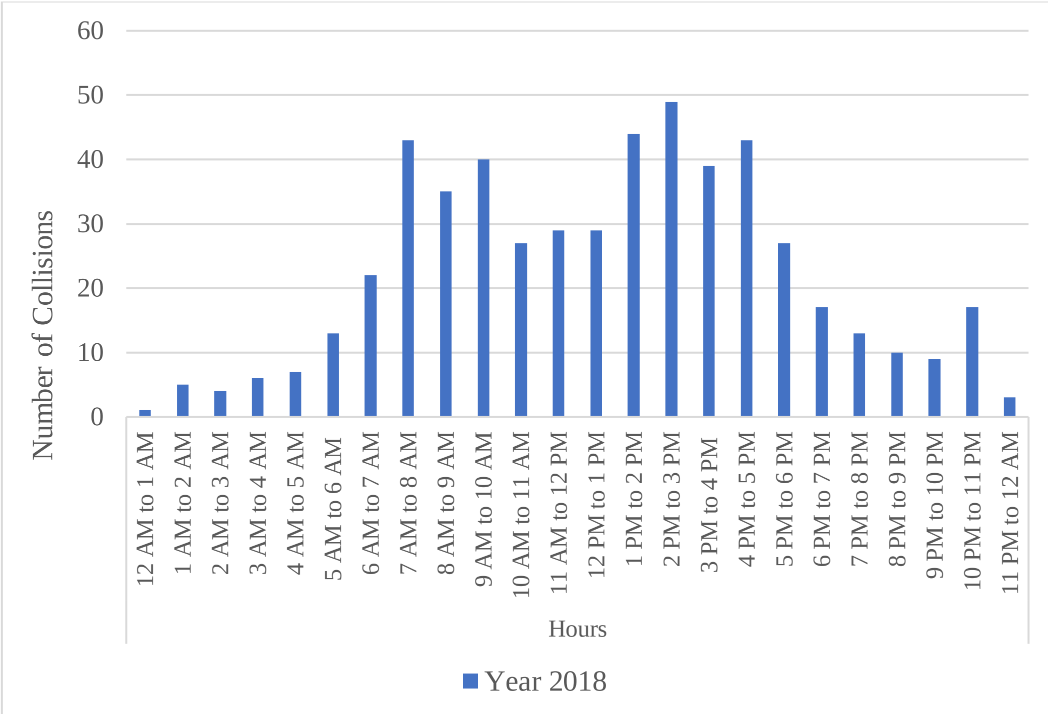



Figure 4-3 (a): Hourly collision distribution for trucks in 2018

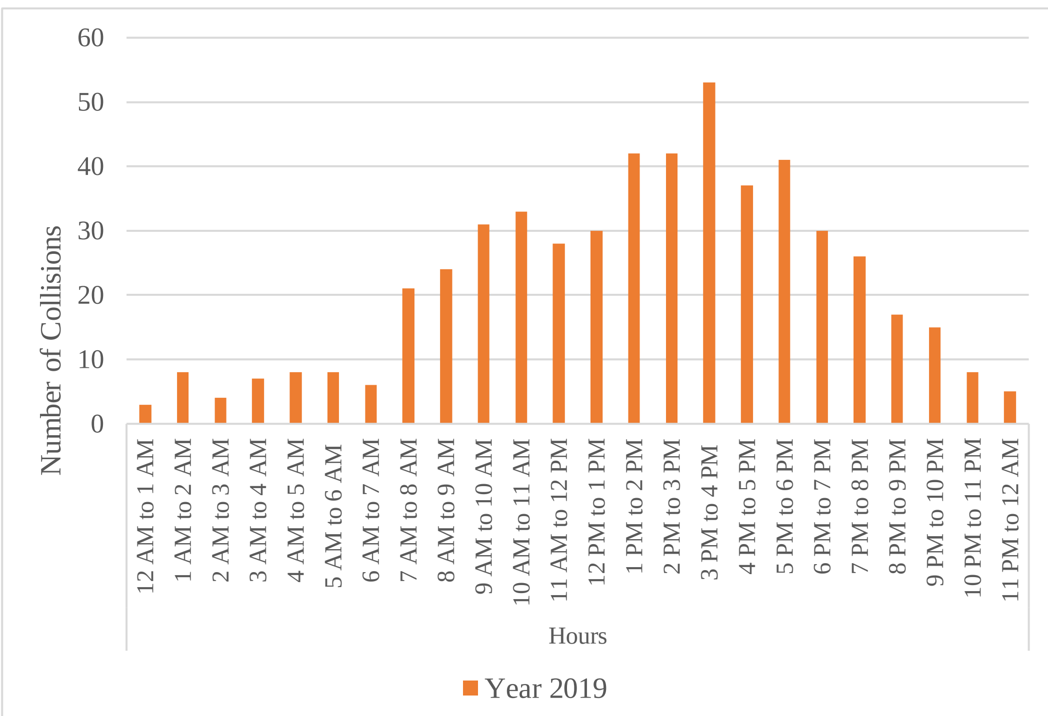



Figure 4-3 (b): Hourly collision distribution for trucks in 2019

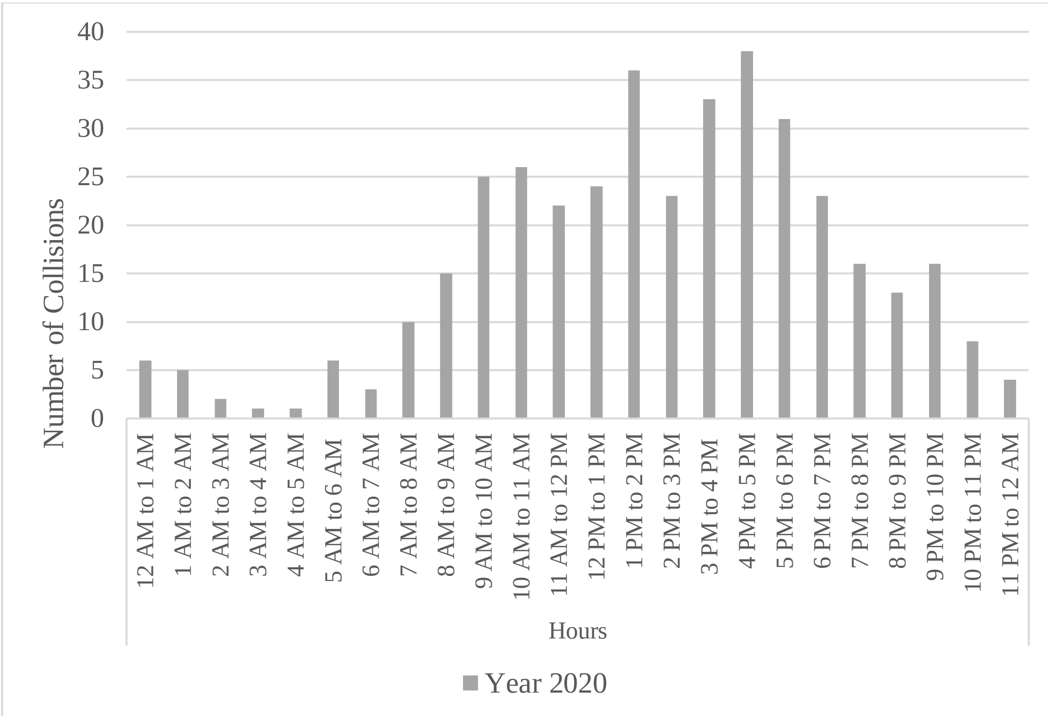



Figure 4-3 (c): Hourly collision distribution for trucks in 2020

The peak hours for cars typically coincide with rush hour periods, which occur during the morning (7:00 AM to 9:00 AM) and evening (4:00 PM to 6:00 PM) when people are commuting to and from work. These peak hours see an increase in cars on the road, leading to congestion and a higher risk of collisions. However, the peak hours for trucks may differ based on the type of freight they transport and the industry they serve. It is evident from Table 4-2 and Figure 4-3 that the majority of truck collisions were observed in the afternoon between 1:00 PM and 4:00 PM. Trucks involved in delivering goods in urban areas tend to avoid morning and evening rush hours (Hunt and Stefan, 2007). Hence, there is often a significant increase in the movement of trucks during afternoon hours that corresponds with the graphs plotted in this analysis.

A chi-square test was conducted on the hourly collisions data to determine whether there is a significant association between the number of collisions and the hour of the day. The chi-square test is a statistical technique used to assess and compare relationships between categorical variables (hour of the day in this case) (Peck et al., 2015). Some of the advantages of conducting chi-square test are as follows:

1. **Non-Parametric Test:** A chi-square test is a non-parametric test, which signifies that it does not require a distribution to meet the required assumptions (Field, 2013).

2. **Identify Association:** The test is used to evaluate whether there is a significant relationship between two variables. It can help identify associations or dependencies between collisions and time of the day (Zar, 1999).

3. **Easy to interpret:** The chi-square test uses a p-value, making it easy to interpret the results in terms of statistical significance (Peck et al., 2015).

4. **Goodness-of-Fit:** The chi-square test compares the distributions of two or more groups and can be useful in determining whether an observed frequency distribution matches an expected distribution (Liu and Agresti, 2005).

5. **Hypotheses Testing:** Chi-square tests can be used to test hypotheses about categorical data, such as evaluating the number of collisions based on time of the day (Rana and Singhal, 2015).

The chi-square test is mathematically represented as (Chi Square Statistics, 2022):

$$\chi^2 = \frac{(O-E)^2}{E} \qquad \text{[Equation 10]}$$

Where:

$\chi^2$ is the chi-square statistic

O is the observed value

E is the expected value

Table 4-3 shows the chi-square test outcomes for hourly collision data.

Table 4-3: Chi-square test for hourly truck collisions in Region of Peel

| | **Value** | **df** | **Asymptotic Significance (2-sided)** |
|---|---|---|---|
| Pearson Chi-Square | 84.715 | 46 | 0.000 |
| N of Valid Cases | 1,446 | | |

**Purpose 1:** To study the relation between number of collisions and hour of the day.

**Null Hypothesis (H0):** The number of collisions is equally distributed across hour of the day.

**Alternative Hypothesis (H1):** The number of collisions is not equally distributed across the hour of the day.

**Inference:** Chi squared equalled 84.715 and the two-tailed p-value was less than 0.0001. As the p-value is less than 0.05, the null hypothesis is rejected. We can infer that the number of collisions was statistically different with changes in hour of the day. The collisions were not equally distributed over the 24-hour time spans.

The hourly data were grouped into time periods to observe travel patterns for trucks that can influence collisions. This approach was adopted to avoid missing truck collisions as trucks might have a different peak period of travel compared to passenger cars. The following time periods were used:

1. AM Peak – 6:00 AM to 10:00 AM
2. Mid-day – 10:00 AM to 3:00 PM
3. PM Peak – 3:00 PM to 7:00 PM
4. Off-peak – 7:00 PM to 6:00 AM

These time periods are consistent with the distribution used by researchers in previous studies (Eisele et. al., 2016) and are representative of all the variations of hours in a day (National Association of City Transportation Officials, 2022).

Table 4-4 shows the collisions observed in Peel Region by time period for 2018, 2019 and 2020. Figure 4-4 shows the same data in a bar graph. This analysis considered all 24 hours of the day, i.e., non-peak periods as well as morning and evening peak periods, and divided the day into four time periods as shown.

Table 4-4: Truck collisions in Region of Peel by time period

| Time Period | Year of Collision | | | Total | Average |
|---|---|---|---|---|---|
| | 2018 | 2019 | 2020 | | |
| AM (6 AM to 10 AM) | 138 | 89 | 48 | 275 | 92 |
| Mid-Day (10 AM to 3 PM) | 187 | 159 | 138 | 484 | 161 |
| PM (3 PM to 7 PM) | 115 | 171 | 126 | 412 | 137 |
| Off Peak (7 PM to 6 AM) | 92 | 108 | 75 | 275 | 92 |
| **Total** | **532** | **527** | **387** | **1446** | |

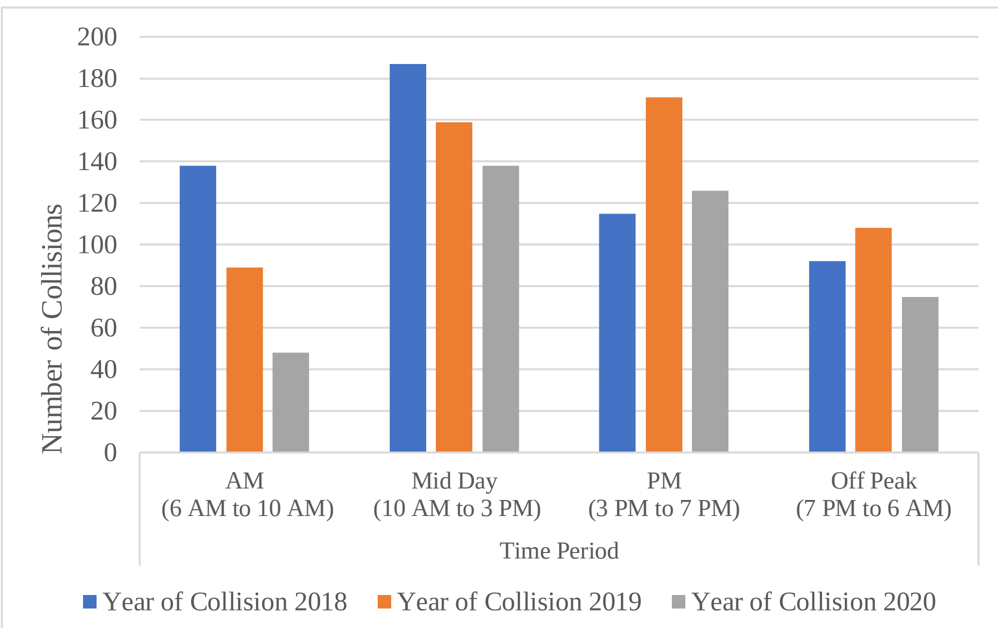



Figure 4-4: Truck collisions in Region of Peel by time period

It is evident from Figure 4-4 and Table 4-4 that the majority of collisions in Region of Peel occurred in the mid-day and PM peak periods. Figure 4-5 shows the average number of collisions observed in the Region of Peel for the four time periods.

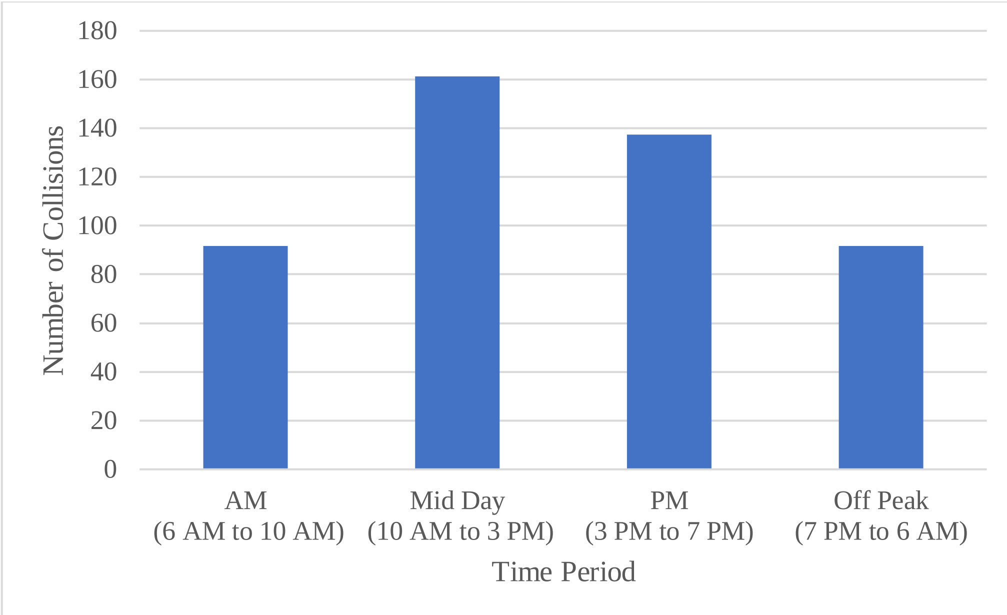



Figure 4-5: Average truck collisions by time period over three years

Single unit commercial vehicles (Class 5 to 7), also known as delivery trucks, are the main freight transportation vehicles used in urban areas of the Region of Peel. These trucks are smaller in size compared to multi-trailer trucks (Class 8 to 13) (Nevland et al., 2020). According to a study conducted by Transportation Canada, cars travel 77 percent of their distance during the day whereas delivery trucks travel 87 percent of their distance during the day and multi-trailer trucks travel 68 percent. Trucks on urban arterial roads are more likely to travel in afternoon peak periods compared to multi-trailer trucks that mainly travel at night. Trucks on freeways travel about 12 percent of their total distance between midnight and 6:00 AM, compared with only 4 percent for delivery trucks and 3 percent for cars (Baldwin, 2005). These results suggest that the high collision rate in the afternoon peak period corresponds with the high volume of trucks expected in the afternoon time period.

A chi-square test was conducted on the collisions data to analyze and determine whether there was a significant association between the number of collisions and the four time periods (AM, mid-day, PM, and off peak). Table 4-5 shows the results of the chi-square test.

Table 4-5: Chi-square test for truck collisions in the Region of Peel based on the four time periods

| | **Value** | **df** | **Asymptotic Significance (2-sided)** |
|---|---|---|---|
| Pearson Chi-Square | 41.709 | 6 | 0.000 |
| N of Valid Cases | 1446 | | |

**Purpose 2:** To study the relationship between number of collisions and the four time periods.

**Null Hypothesis (H0):** The number of collisions is equally distributed across the four time periods.

**Alternative Hypothesis (H1):** The number of collisions is not equally distributed across the four time periods.

**Inference:** Chi squared equalled 41.709 and the two-tailed p-value was less than 0.0001. As the p-value was less than 0.05, the null hypothesis was rejected. We can infer that the number of collisions was statistically different for the four time periods, i.e, the collisions were not equally distributed over the four time periods.

Collisions were also analysed against external factors such as weather conditions, lighting and pavement surface conditions. External conditions play a vital role in determining the frequency and severity of truck collisions. Adverse conditions can significantly impede visibility for drivers and reduce vehicle stability (Haq et al., 2022).

Adverse weather conditions such as rain, snow, wind, and fog can increase the risk of collisions especially for trucks that require a longer stopping distance and intricate manoeuvring owing to their substantial weight and size.

Table 4-6 shows truck collisions in the Region of Peel from 2018 to 2020 by weather conditions. Table 4-7 shows the frequency and proportion of collisions by weather conditions. This information can provide a start to understanding whether weather conditions contribute to truck collisions.

Table 4-6: Truck collisions in Region of Peel by weather conditions

| **Year of Collision** | **Weather Condition** | | | | | | | | **Total** |
|---|---|---|---|---|---|---|---|---|---|
| | **Clear** | **Rain** | **Snow** | **Freezing Rain** | **Drifting Snow** | **Wind** | **Fog** | **Other** | |
| 2018 | 473 | 39 | 14 | 0 | 2 | 0 | 1 | 3 | 532 |
| 2019 | 451 | 37 | 27 | 4 | 5 | 0 | 2 | 1 | 527 |
| 2020 | 346 | 20 | 14 | 2 | 2 | 1 | 1 | 1 | 387 |
| **Total** | **1,270** | **96** | **55** | **6** | **9** | **1** | **4** | **5** | **1,446** |

Table 4-7: Frequency and percentage of truck collisions in Region of Peel by weather condition

| Weather Condition | Frequency | Percent |
|---|---|---|
| Clear | 1,270 | 87.8 |
| Rain | 96 | 6.6 |
| Snow | 55 | 3.8 |
| Freezing Rain | 6 | 0.4 |
| Drifting Snow | 9 | 0.6 |
| Wind | 1 | 0.1 |
| Fog | 4 | 0.3 |
| Other | 5 | 0.3 |
| **Total** | **1,446** | **100** |

Table 4-6 and Table 4-7 show that around 88 percent of truck collisions took place in clear weather. Approximately 7 percent and 4 percent of truck collisions were observed in rain and snow respectively. A slippery road surface from rain and snow can amplify the risk of truck collision by increasing braking distance by 3 to 12 times, which can lead to rear-end collisions and loss of vehicle control (IHSA, 2019). A negligible number of truck collisions (less than 1 percent for each condition) were observed in other weather conditions (freezing rain, drifting snow, wind, and fog) in the Region of Peel. The lower number of truck collisions observed during adverse weather conditions can be attributed to the lower number of trips undertaken in those conditions. The data can provide a start to understanding whether weather conditions contribute to truck collisions.

Lighting conditions can contribute to truck collisions by affecting visibility and glare. Low light or inadequate lighting can make it difficult for truck drivers to identify pedestrians, cyclists and other motor vehicles and increase the risk of collisions.

Table 4-8 shows truck collisions in the Region of Peel between 2018 and 2020 by lighting condition. Table 4-9 shows the frequency and proportion of collisions by lighting condition. The data can provide a start to understanding whether lighting conditions contribute to truck collisions.

Table 4-8: Truck collisions in Region of Peel by lighting condition

| **Year of Collision** | **Lighting Condition** | | | | | | | **Total** |
|---|---|---|---|---|---|---|---|---|
| | **Daylight** | **Daylight Artificial** | **Dawn** | **Dusk** | **Dusk Artificial** | **Dark** | **Dark Artificial** | |
| 2018 | 394 | 1 | 30 | 9 | 1 | 46 | 51 | 532 |
| 2019 | 378 | 8 | 9 | 28 | 0 | 69 | 35 | 527 |
| 2020 | 284 | 2 | 5 | 13 | 1 | 54 | 28 | 387 |
| **Total** | **1056** | **11** | **44** | **50** | **2** | **169** | **114** | **1446** |

Table 4-9: Frequency and percentage of truck collisions in Region of Peel by lighting condition

| **Lighting Condition** | **Frequency** | **Percent** |
|---|---|---|
| Daylight | 1,056 | 73.0 |
| Daylight Artificial | 11 | 0.8 |
| Dawn | 44 | 3.0 |
| Dusk | 50 | 3.5 |
| Dusk Artificial | 2 | 0.1 |
| Dark | 169 | 11.7 |
| Dark Artificial | 114 | 7.9 |
| **Total** | **1,446** | **100** |

*Appendix IV - Lighting Conditions Description* provides a description of each lighting condition.

Table 4-8 and Table 4-9 show that the majority of truck collisions (77 percent) occurred in daylight. 'Dark' and 'Dark Artificial' lighting conditions also seemed to contribute substantially to truck collisions, with approximately 12 percent and 8 percent truck collisions observed in those lighting conditions. Dark lighting conditions can diminish the contrast between the road and objects, compromising the driver's ability to react to changes in traffic conditions (Uttley and Fotios, 2017). The other lighting conditions appeared to have had a lower impact on truck collisions (less than 4 percent).

Pavement surface conditions can contribute to varying levels of traction on road and can contribute to truck collisions. The likelihood and severity of truck collisions can be affected by pavement surface conditions and maintenance.

Table 4-10 shows truck collisions observed in the Region of Peel from 2018 to 2020 by pavement surface condition. Table 4-11 shows the frequency and proportion of collisions by pavement surface condition. This information can provide a start to understanding whether pavement surface condition contributes to truck collisions.

Table 4-10: Truck collisions in Region of Peel by pavement surface condition

| Year of Collision | Pavement Surface Condition | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|
| | Dry | Wet | Loose Snow | Slush | Packed Snow | Ice | Other | |
| 2018 | 451 | 58 | 15 | 0 | 1 | 4 | 3 | 532 |
| 2019 | 427 | 61 | 17 | 6 | 6 | 9 | 1 | 527 |
| 2020 | 328 | 44 | 9 | 2 | 1 | 3 | 0 | 387 |
| **Total** | **1,206** | **163** | **41** | **8** | **8** | **16** | **4** | **1,446** |

Table 4-11: Frequency and percentage of truck collisions in Region of Peel by pavement surface condition

| **Pavement Surface Condition** | **Frequency** | **Percent** |
|---|---|---|
| Dry | 1206 | 83.4 |
| Wet | 163 | 11.3 |
| Loose Snow | 41 | 2.8 |
| Slush | 8 | 0.6 |
| Packed Snow | 8 | 0.6 |
| Ice | 16 | 1.1 |
| Other | 4 | 0.3 |
| **Total** | **1446** | **100** |

Table 4-10 and Table 4-11 show that a high percentage of truck collisions (83 percent) occurred when the pavement surface was dry. Wet pavement surface conditions were associated with approximately 11 percent of truck collisions. Wet roads can lead to slippery conditions with decreased friction, leading to difficulties in braking, manoeuvring, and maintaining control over the vehicle (Mkwata and Chong, 2022). The other pavement surface conditions appeared to have a comparatively lower impact on truck collisions (less than 3 percent).

## 4.3 Freight Fluidity Data Analysis

This section focuses on using the study's freight fluidity measures (TTI, PTI and BI) to analyze freight fluidity in 2019 and 2020 in the Region of Peel. Temporal and spatial analyses were conducted. Figure 4-6 shows TTI, PTI and BI by municipality.

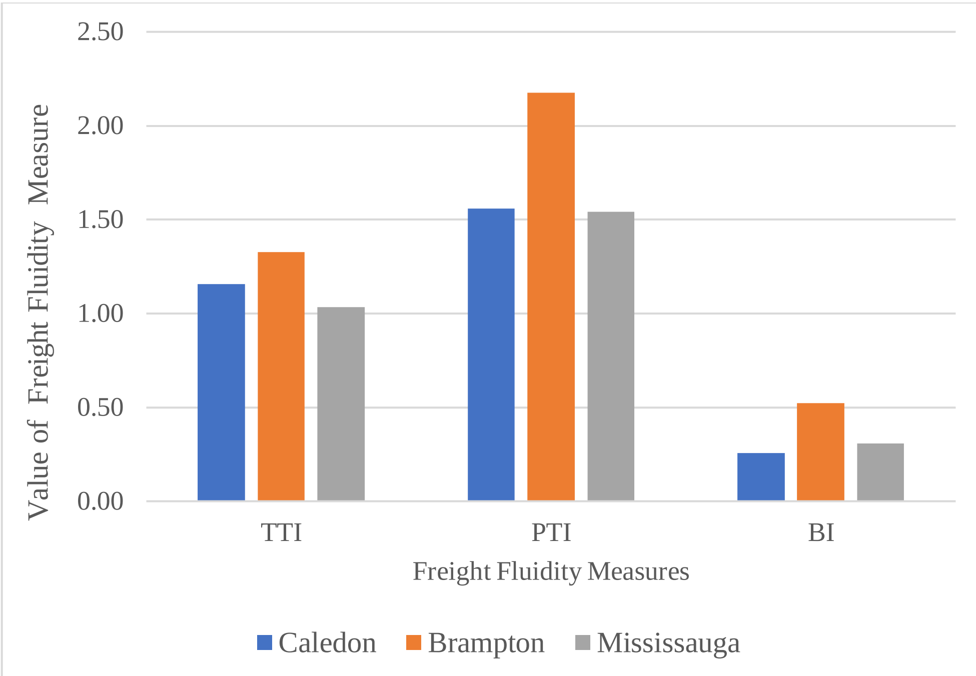



Figure 4-6 (a): Freight fluidity measures by municipality in 2019

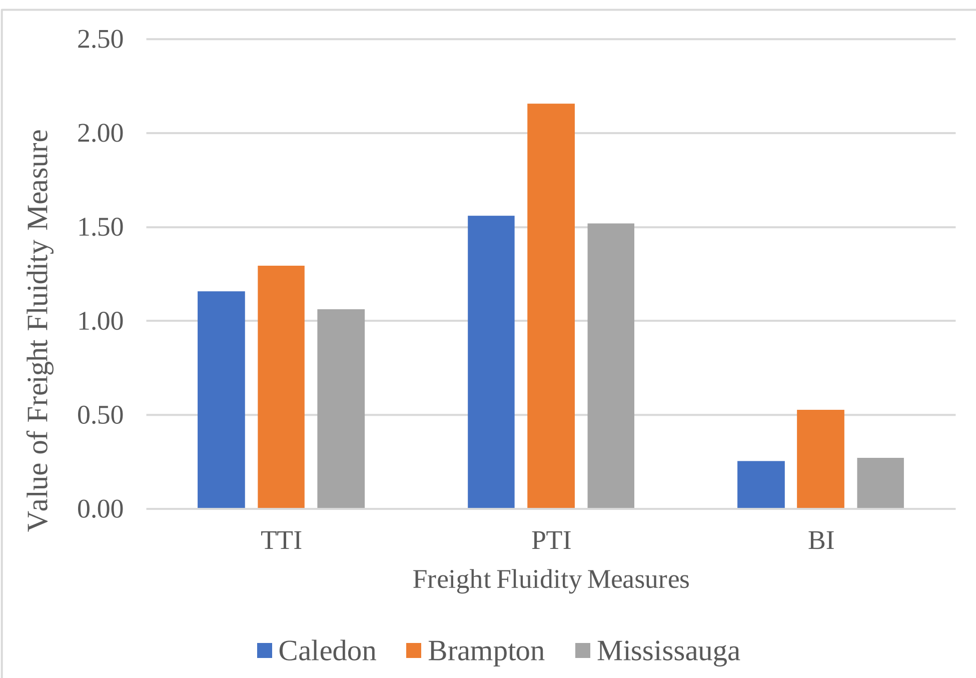



Figure 4-6 (b): Freight fluidity measures by municipality in 2020

Figure 4-6 shows that each freight fluidity measure was higher in Brampton than in Mississauga and Caledon in both 2019 and 2020. Compared to Mississauga and Caledon, the TTI, PTI and BI values for Brampton were around 17 percent, 40 percent, and 100 percent higher respectively.

TTI, PTI and BI were plotted geospatially for 2019 and 2020. The results are shown in Figure 4-7. The values were plotted in the form of bandwidths. Bandwidths play a pivotal role in determining the spatial influence of data points, providing a nuanced understanding of the distribution and impact of freight fluidity measures across the Region of Peel. In this case, the thickness of the bandwidth serves as a visual indicator. A higher value of a freight fluidity measure is indicated by a thicker bandwidth on the map. The bandwidths help emphasize the influence of a freight fluidity measure, leading to a more localized spatial analysis. This geospatial approach enhances the interpretability of the data by indicating regions where the respective freight fluidity measure holds greater significance or impact.

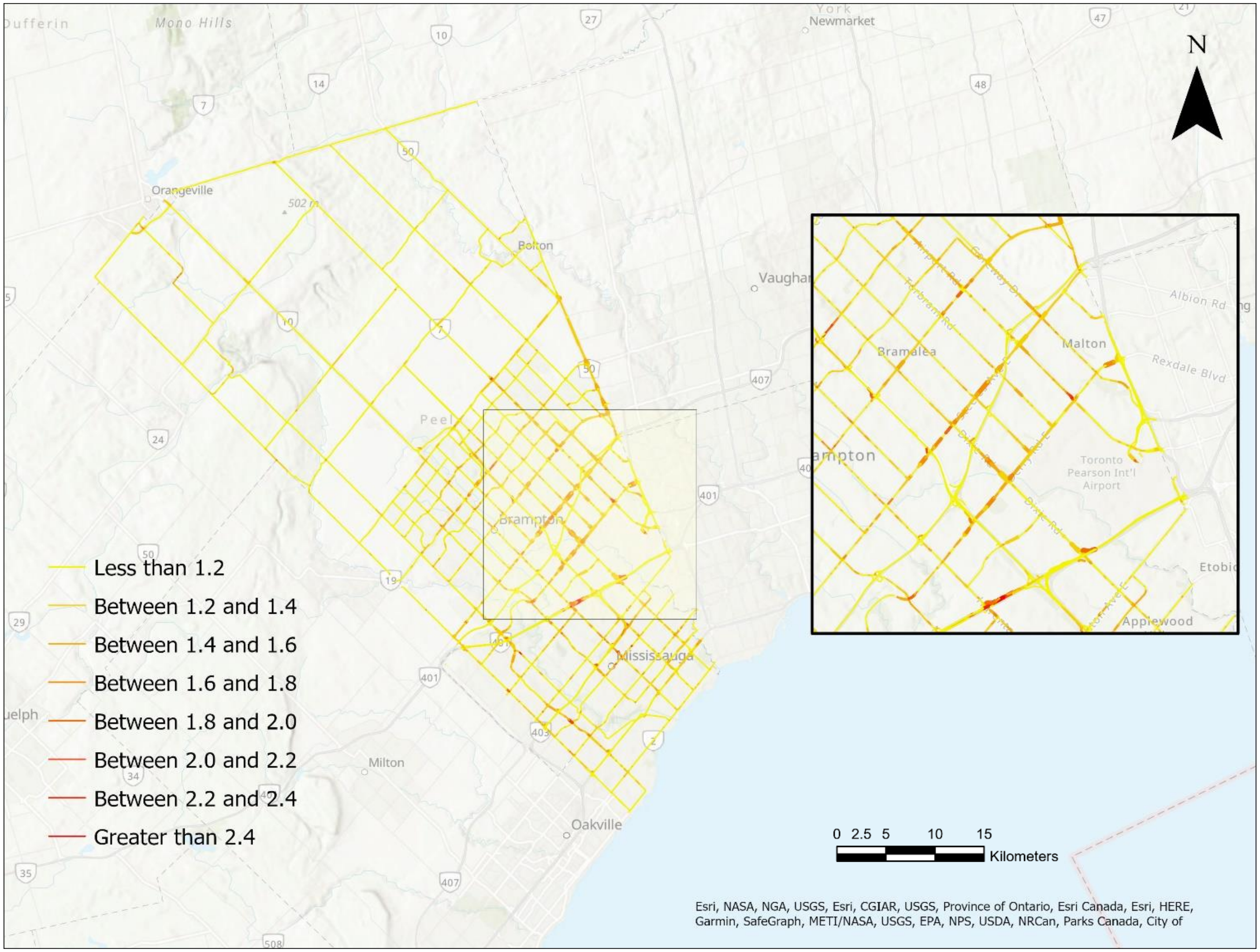



Figure 4-7 (a): Bandwidths showing TTI in 2019

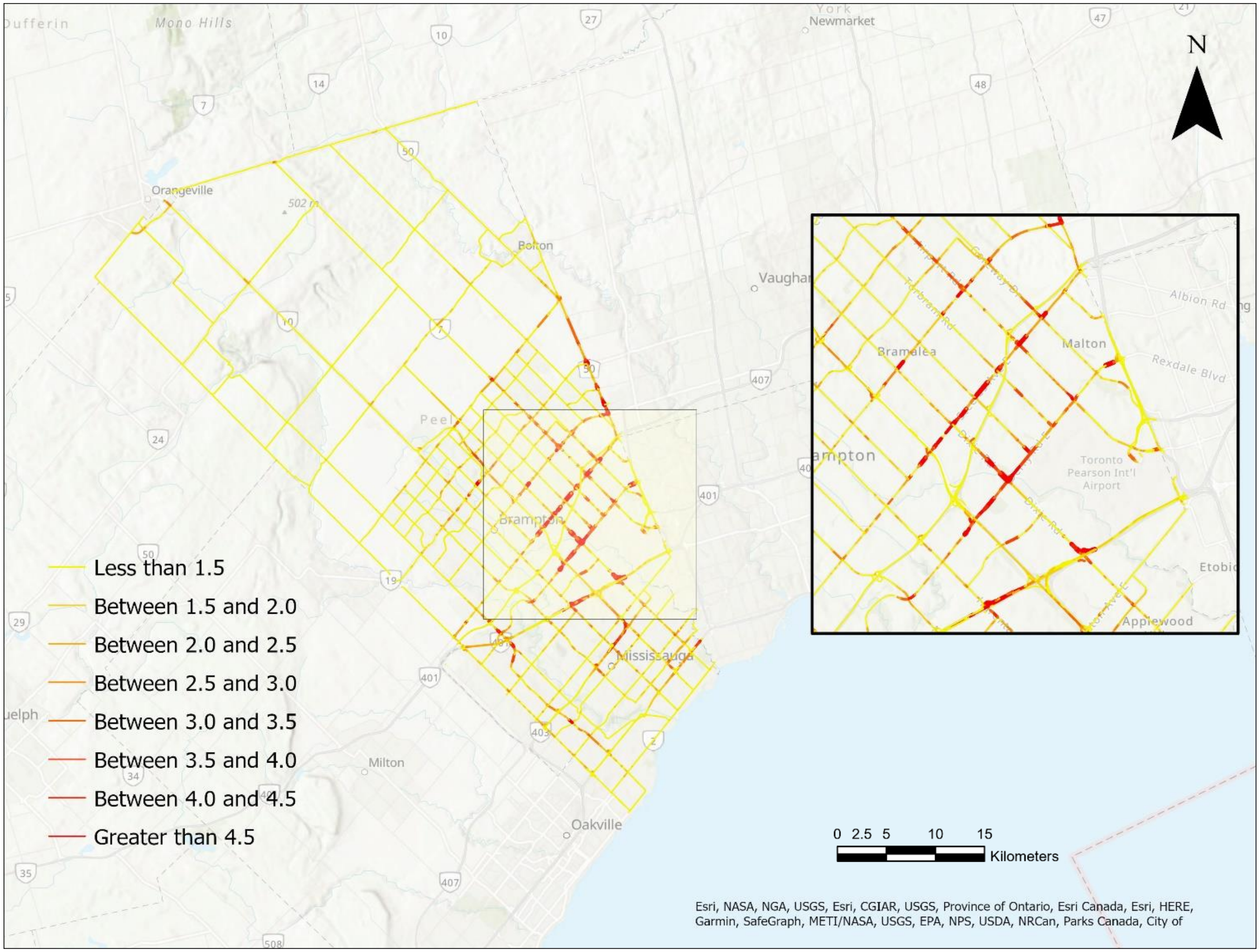



Figure 4-7 (b): Bandwidths showing PTI in 2019

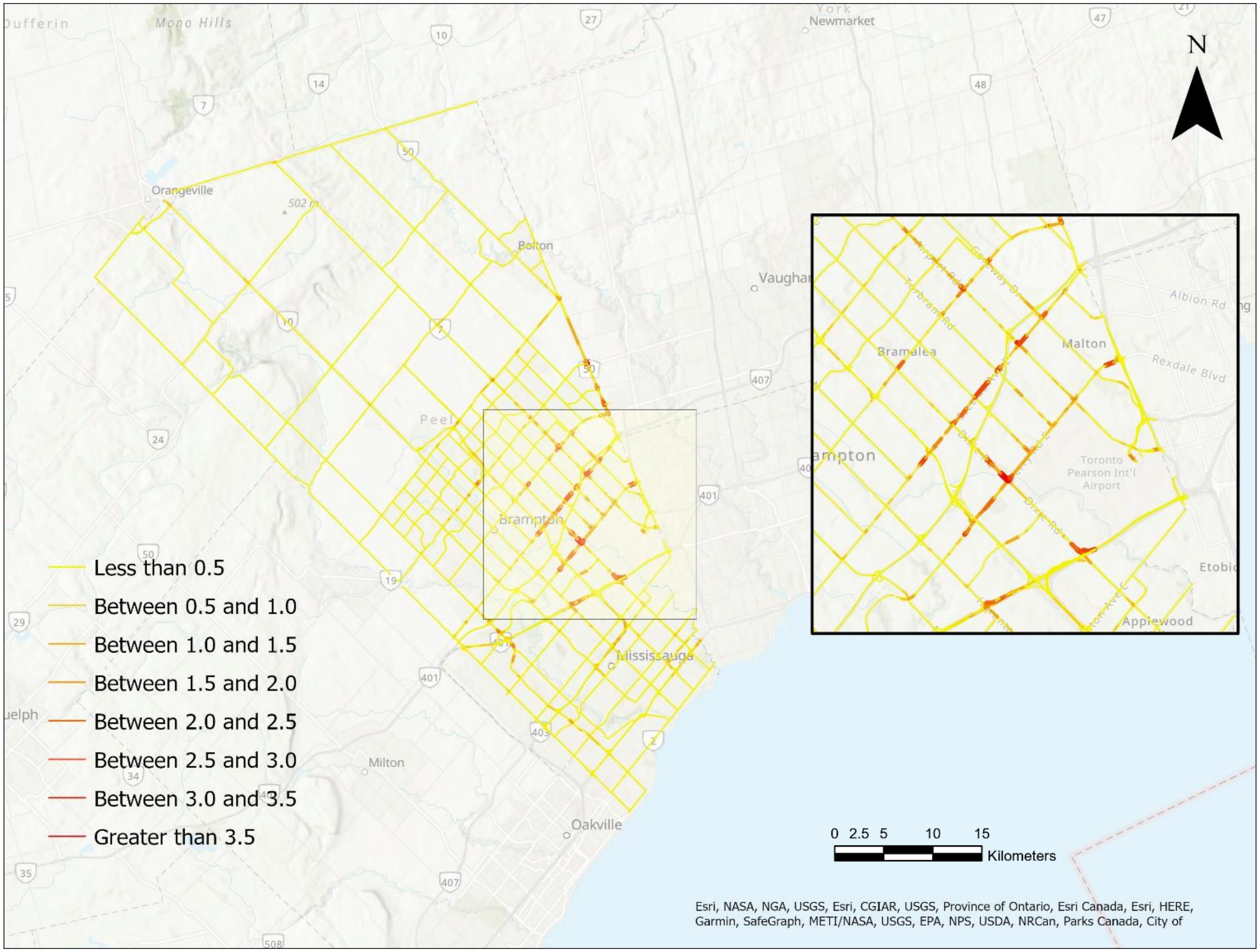



Figure 4-7 (c): Bandwidths showing BI in 2019

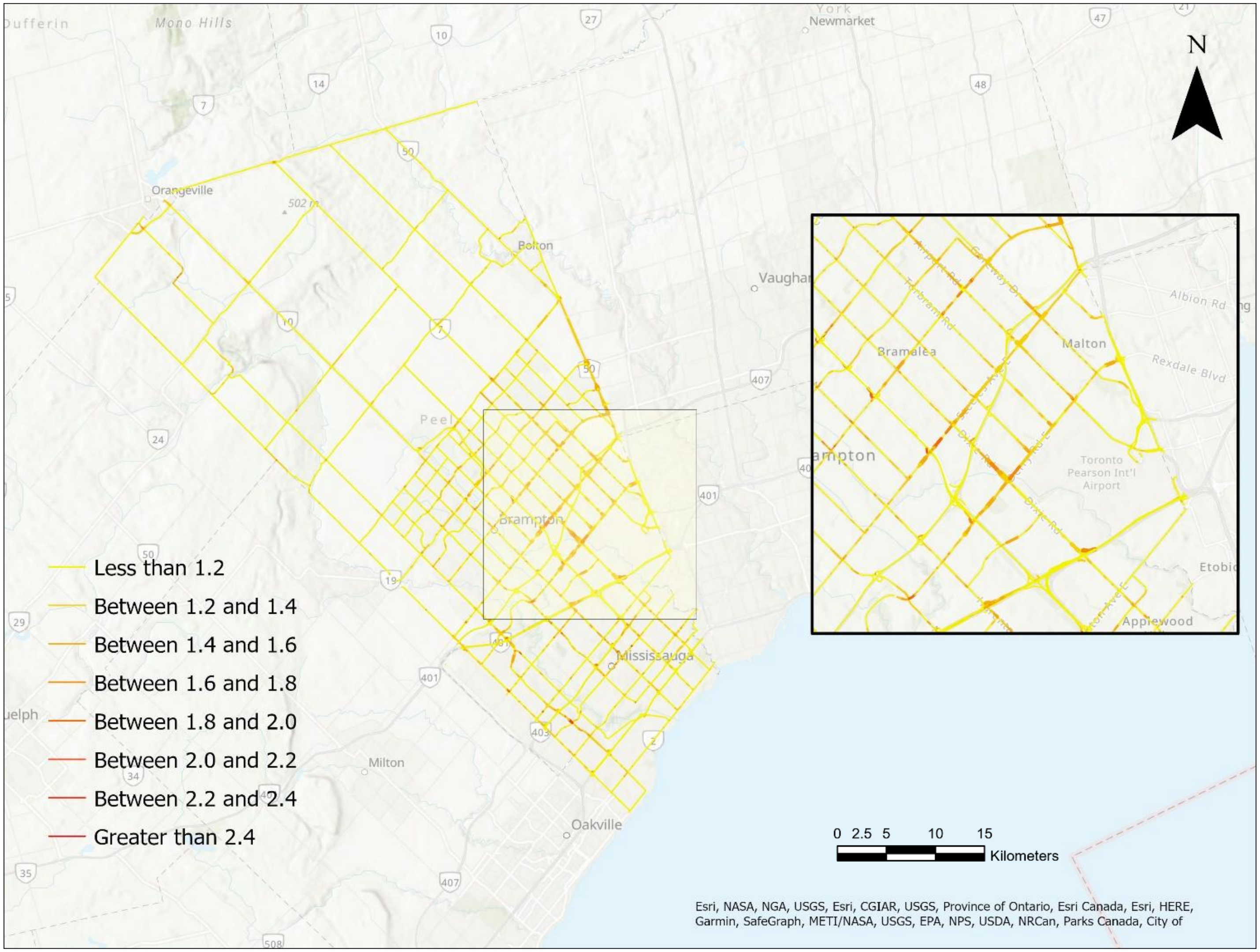



Figure 4-7 (d): Bandwidths showing TTI in 2020

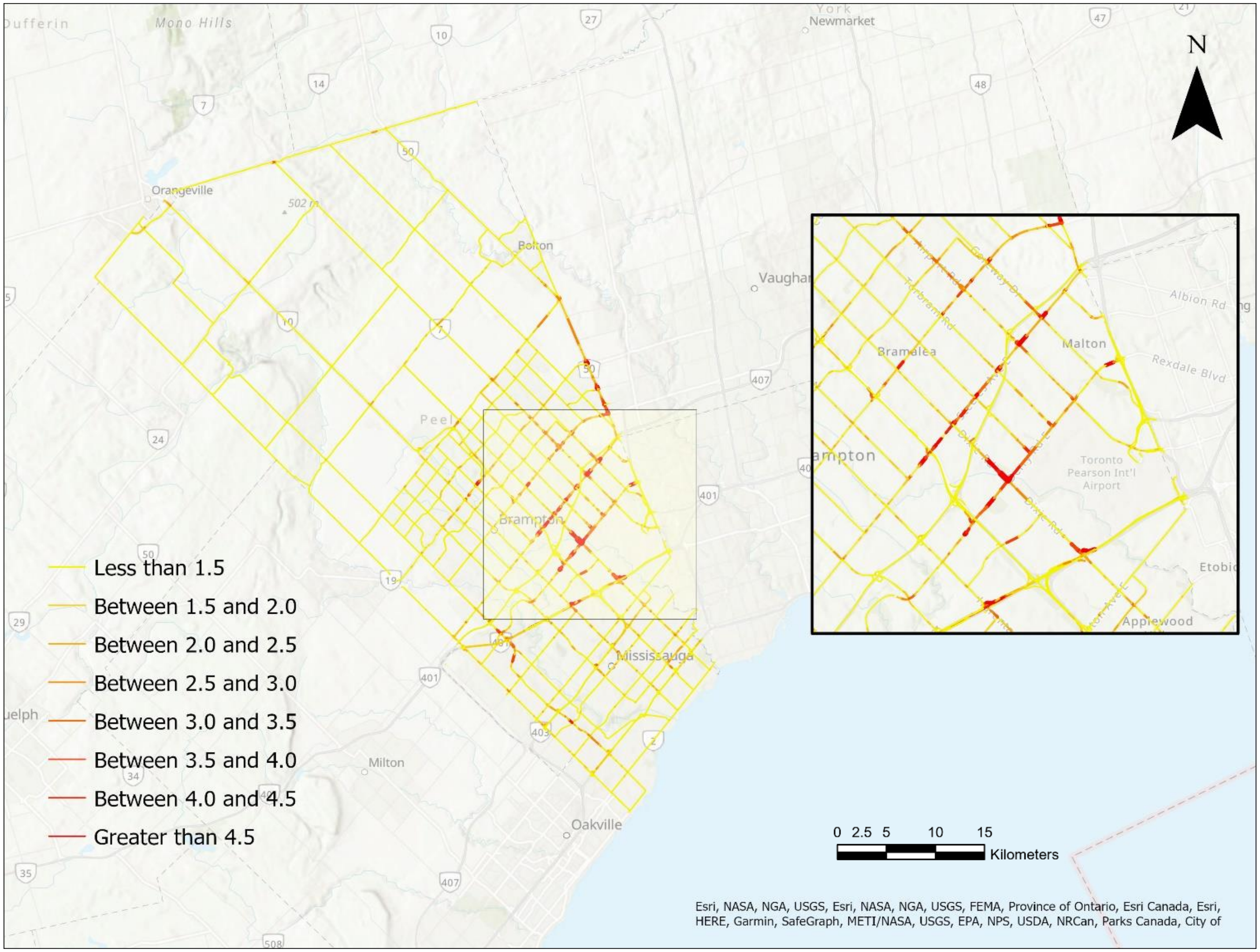



Figure 4-7 (e): Bandwidths showing PTI in 2020

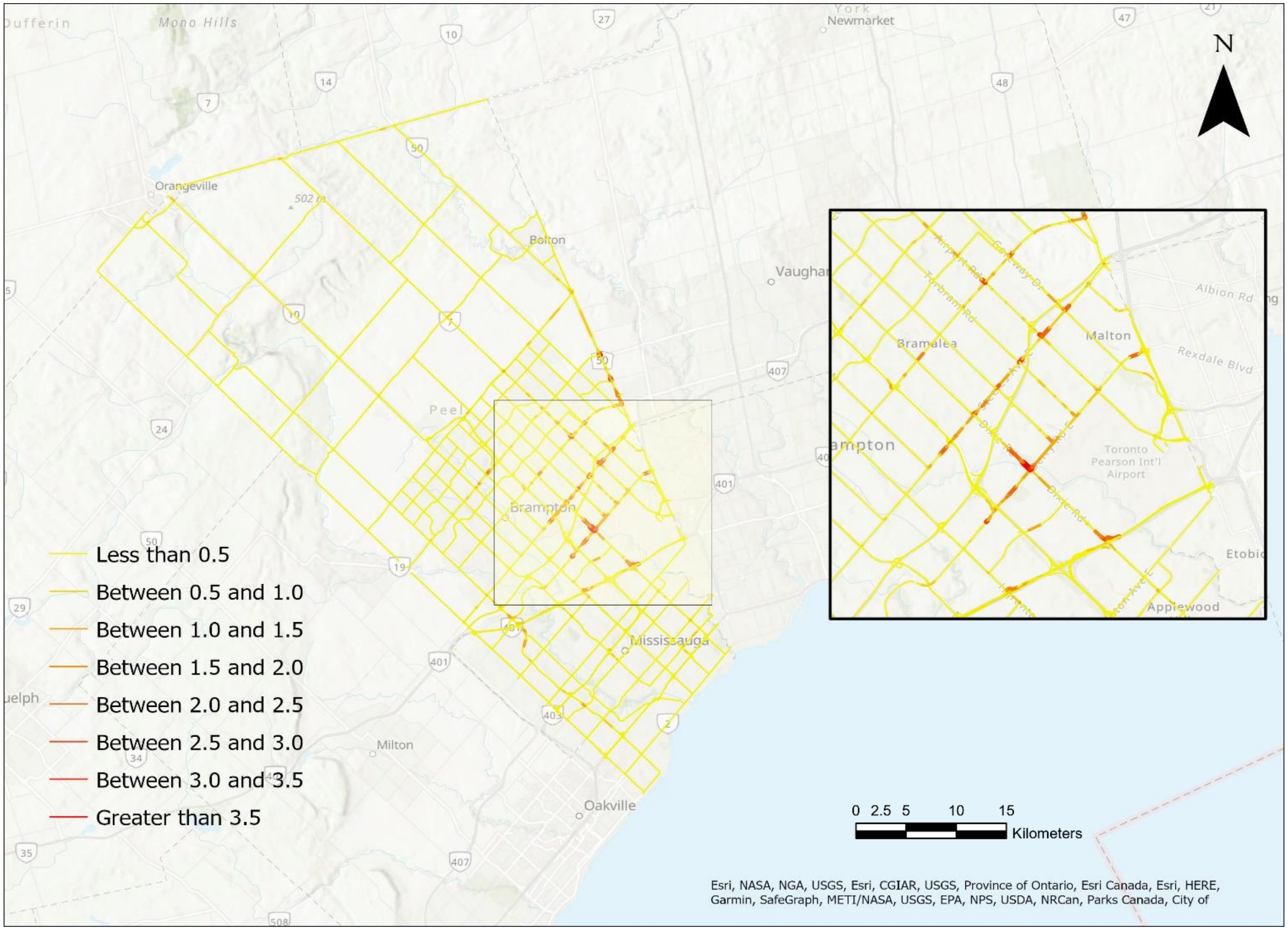



Figure 4-7 (f): Bandwidths showing BI in 2020

As mentioned, the values of the freight fluidity measures were higher in Brampton than in Mississauga and Caledon. In particular, the area around Toronto's Pearson Airport showed a level of congestion higher than in the rest of the Region of Peel. Pearson Airport handles more than 50 percent of all air cargo in Canada. More than 50,000 people are employed at Pearson Airport and commute to and from work each day. In addition, more than 300,000 workers are employed in the Airport Employment Zone (AEZ) (Pearson Airport, 2022). The AEZ is a 15,230-hectare area around Pearson Airport. It is bounded by Highway 10 to the north, Burnhamthorpe Road to the south, Islington Avenue to the east and Hurontario Street to the west (Pearson Connects, 2015). The AEZ includes Canadian National Railway's largest intermodal facility, a vital link for freight transportation (Airport Employment Zone, 2021).

The higher congestion indicated by the higher freight fluidity measures observed around Pearson Airport complements the analysis. The Region of Peel is aware of the congestion concern on roads leading to Pearson Airport. The visual depiction of freight fluidity measures in the dashboard created as a part of this research can help decision makers to make better informed decisions when working to improve mobility to and through the AEZ.

A descriptive analysis was conducted for the 2019 and 2020 freight fluidity measures. Table 4-12 shows the descriptive analysis for the freight fluidity measures for the whole of the Region of Peel. Table 4-13 shows each municipality separately.

Table 4-12 (a): Descriptive statistics for freight fluidity measures for 2019

| 2019 | Mean | | Standard Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|---|
| | Statistic | Standard Error | Statistic | Statistic | Statistic | Standard Error | Statistic | Standard Error |
| TTI | 1.1700 | 0.06998 | 0.35685 | 0.127 | -2.963 | 0.456 | 8.442 | 0.887 |
| PTI | 1.7885 | 0.12905 | 0.65804 | 0.433 | -1.327 | 0.456 | 2.850 | 0.887 |
| BI | 0.3809 | 0.04994 | 0.25463 | 0.065 | 0.859 | 0.456 | 0.441 | 0.887 |

Table 4-12 (b): Descriptive statistics for freight fluidity measures for 2020

| 2020 | Mean | | Standard Deviation | Variance | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|---|---|
| | Statistic | Standard Error | Statistic | Statistic | Statistic | Standard Error | Statistic | Standard Error |
| TTI | 1.1700 | 0.07176 | 0.36588 | 0.134 | -2.737 | 0.456 | 7.322 | 0.887 |
| PTI | 1.7727 | 0.15049 | 0.76735 | 0.589 | -0.453 | 0.456 | 1.248 | 0.887 |
| BI | 0.3658 | 0.06218 | 0.31707 | 0.101 | 1.044 | 0.456 | 0.777 | 0.887 |

Table 4-13 (a): Descriptive statistics by municipality for 2019

| 2019 | | Standard Error | 95 percent Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|
| | | | Lower Bound | Upper Bound | | |
| TTI | Brampton | 0.02758 | 1.2646 | 1.3893 | 1.25 | 1.51 |
| | Caledon | 0.02763 | 1.0793 | 1.2328 | 1.06 | 1.23 |
| | Mississauga | 0.15516 | 0.6880 | 1.3794 | 0.00 | 1.40 |
| | Total | 0.06998 | 1.0259 | 1.3142 | 0.00 | 1.51 |
| PTI | Brampton | 0.11911 | 1.9062 | 2.4451 | 1.56 | 2.85 |
| | Caledon | 0.06194 | 1.3867 | 1.7306 | 1.32 | 1.68 |
| | Mississauga | 0.25291 | 0.9776 | 2.1047 | 0.00 | 2.68 |
| | Total | 0.12905 | 1.5227 | 2.0543 | 0.00 | 2.85 |
| BI | Brampton | 0.07474 | 0.3544 | 0.6926 | 0.20 | 0.96 |
| | Caledon | 0.02353 | 0.1921 | 0.3227 | 0.18 | 0.31 |
| | Mississauga | 0.08357 | 0.1213 | 0.4937 | 0.00 | 0.98 |
| | Total | 0.04994 | 0.2781 | 0.4838 | 0.00 | 0.98 |

Table 4-13 (b): Descriptive statistics by municipality for 2020

| 2020 | | Standard Error | 95 percent Confidence Interval for Mean | | Minimum | Maximum |
|---|---|---|---|---|---|---|
| | | | Lower Bound | Upper Bound | | |
| TTI | Brampton | 0.04245 | 1.1996 | 1.3917 | 1.00 | 1.45 |
| | Caledon | 0.04877 | 1.0225 | 1.2933 | 1.02 | 1.31 |
| | Mississauga | 0.16090 | 0.7026 | 1.4196 | 0.00 | 1.44 |
| | Total | 0.07176 | 1.0222 | 1.3177 | 0.00 | 1.45 |
| PTI | Brampton | 0.22283 | 1.6528 | 2.6609 | 1.00 | 3.49 |
| | Caledon | 0.20211 | 0.9979 | 2.1202 | 1.03 | 2.15 |
| | Mississauga | 0.25283 | 0.9572 | 2.0838 | 0.00 | 2.62 |
| | Total | 0.15049 | 1.4627 | 2.0826 | 0.00 | 3.49 |
| BI | Brampton | 0.11636 | 0.2628 | 0.7893 | 0.00 | 1.21 |
| | Caledon | 0.09630 | -0.0138 | 0.5209 | 0.01 | 0.51 |
| | Mississauga | 0.07924 | 0.0945 | 0.4476 | 0.00 | 0.94 |
| | Total | 0.06218 | 0.2377 | 0.4938 | 0.00 | 1.21 |

Table 4-12 and Table 4-13 show that TTI, PTI and BI remained quite consistent between 2019 and 2020 with less than a 10 percent difference observed. This suggests that the pandemic did not have a major impact on congestion. Unlike collisions, which showed a sharp decline during the pandemic, the freight fluidity measures remained consistent. Brampton showed the highest impedance to mobility, as reflected by a higher 95 percent confidence interval for all freight fluidity measures compared to Mississauga and Caledon in both 2019 and 2020.

The freight fluidity measures in Table 4-12 and Table 4-13 showed a high level of skewness and kurtosis. A high level of skewness (less than -1 or greater than 1) shows a high level of asymmetry of a probability distribution around its mean. Skewness is given by the following equation:

$$\mu = \frac{\sum_{i=1}^{n}(xi - \bar{x})^3}{(N-1) * \sigma} \qquad \text{[Equation 11]}$$

Where:

μ is the skewness

**σ** is the standard deviation

x̄ is the mean of the distribution

$x_i$ is the random variable

N is the number of variables

Kurtosis is a statistical measure used to find the extent to which data are concentrated or dispersed at the tails of a probability distribution. A positive value indicates a peaked distribution, and a negative value indicates a flatter distribution. Data sets with high positive kurtosis are likely to have thick tails indicating extreme outliers, whereas data sets with low negative kurtosis tend to have thin tails indicating lack of outliers. *Appendix V – Outliers for 2019 and 2020* gives the outliers.

Kurtosis is given by the following equation:

$$K = \frac{\sum_{i=1}^{n}(xi - \bar{x})^4}{(n - \sigma)^4} \qquad \text{[Equation 12]}$$

Where:

K is the kurtosis

σ is the standard deviation

$\bar{x}$ is the mean of the distribution

$x_i$ is the data point

n is the number of data points

In order to make the results more robust, the freight fluidity measures at the 50$^{th}$ and 85$^{th}$ percentile were analyzed. Table 4-14 shows the freight fluidity measures (TTI, PTI and BI) at the 50$^{th}$ and 85$^{th}$ percentile respectively. Figure 4-8 shows the corresponding freight fluidity measures in a bar chart at the 50$^{th}$ and 85$^{th}$ percentile respectively.

*Appendix VI – Freight Fluidity Measures Frequency Distribution for 50$^{th}$ percentile and 85$^{th}$ percentile* shows the frequency distributions for the freight fluidity measures.

Table 4-14 (a): Descriptive statistics for TTI for 2019 and 2020 at the 50$^{th}$ and 85$^{th}$ percentile

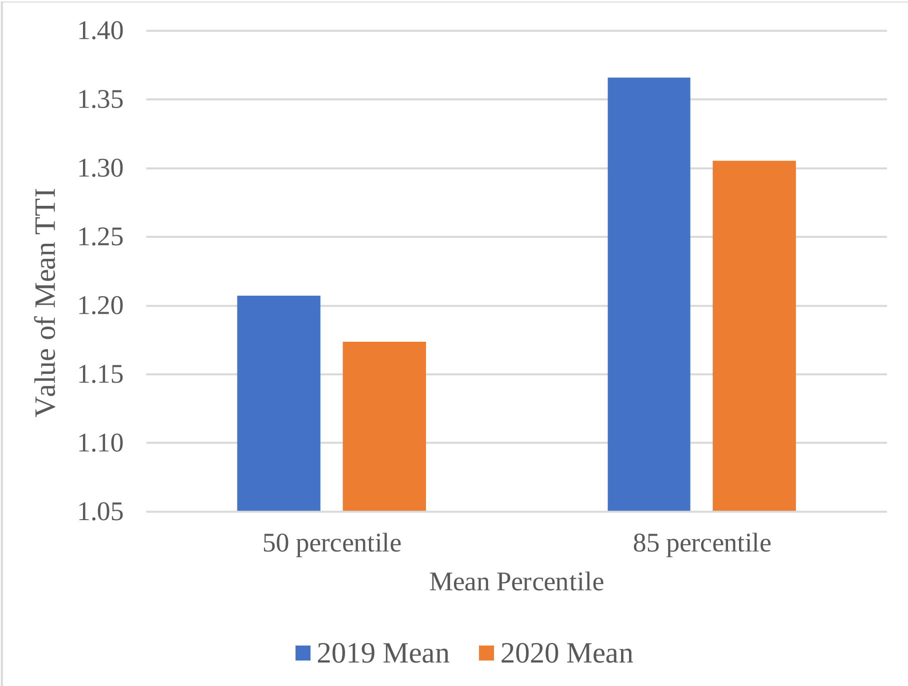
| | | **TTI 2019 50$^{th}$ percentile** | **TTI 2019 85$^{th}$ percentile** | **TTI 2020 50$^{th}$ percentile** | **TTI 2020 85$^{th}$ percentile** |
|---|---|---|---|---|---|
| N | Valid | 11274 | 11274 | 11274 | 11274 |
| | Missing | 0 | 0 | 0 | 0 |
| Mean | | 1.207146 | 1.366031 | 1.173857 | 1.305588 |
| Standard Deviation | | 0.1740930 | 0.3588234 | 0.1536786 | 0.3136094 |
| Skewness | | 1.641 | 2.395 | 1.658 | 1.987 |
| Standard Error of Skewness | | 0.023 | 0.023 | 0.023 | 0.023 |
| Kurtosis | | 5.081 | 13.637 | 4.544 | 7.082 |
| Standard Error of Kurtosis | | 0.046 | 0.046 | 0.046 | 0.046 |

Table 4-14 (b): Descriptive statistics for PTI for 2019 and 2020 at the 50th and 85th percentile

| | | **PTI 2019 50th percentile** | **PTI 2019 85th percentile** | **PTI 2020 50th percentile** | **PTI 2020 85th percentile** |
|---|---|---|---|---|---|
| N | Valid | 11274 | 11274 | 11274 | 11274 |
| | Missing | 0 | 0 | 0 | 0 |
| Mean | | 1.586425 | 1.884425 | 1.421055 | 1.601002 |
| Standard Deviation | | 0.7994471 | 2.0737248 | 0.5626437 | 1.2771247 |
| Skewness | | 3.704 | 9.468 | 3.667 | 9.801 |
| Standard Error of Skewness | | 0.023 | 0.023 | 0.023 | 0.023 |
| Kurtosis | | 21.322 | 123.352 | 19.595 | 133.850 |
| Standard Error of Kurtosis | | 0.046 | 0.046 | 0.046 | 0.046 |

Table 4-14 (c): Descriptive statistics for BI for 2019 and 2020 at the 50th and 85th percentile

| | | **BI 2019 50th percentile** | **BI 2019 85th percentile** | **BI 2020 50th percentile** | **BI 2020 85th percentile** |
|---|---|---|---|---|---|
| N | Valid | 11274 | 11274 | 11274 | 11274 |
| | Missing | 0 | 0 | 0 | 0 |
| Mean | | 0.214832 | 0.284382 | 0.153483 | 0.189301 |
| Standard Deviation | | 0.3659874 | 0.7965988 | 0.2889512 | 0.6177722 |
| Skewness | | 3.863 | 6.836 | 4.905 | 8.773 |
| Standard Error of Skewness | | 0.023 | 0.023 | 0.023 | 0.023 |
| Kurtosis | | 20.308 | 60.932 | 34.347 | 101.988 |
| Standard Error of Kurtosis | | 0.046 | 0.046 | 0.046 | 0.046 |



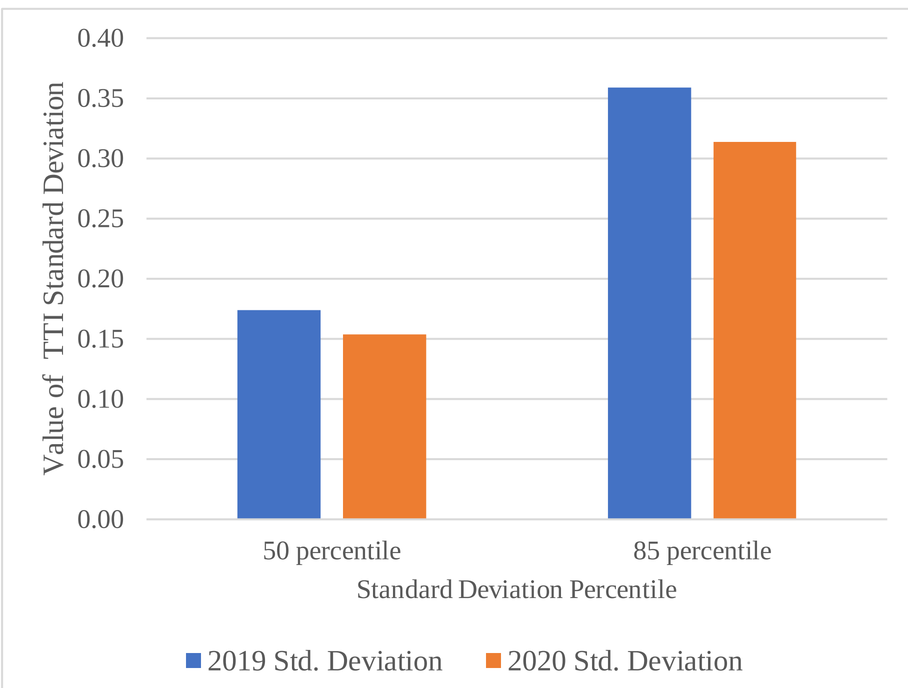
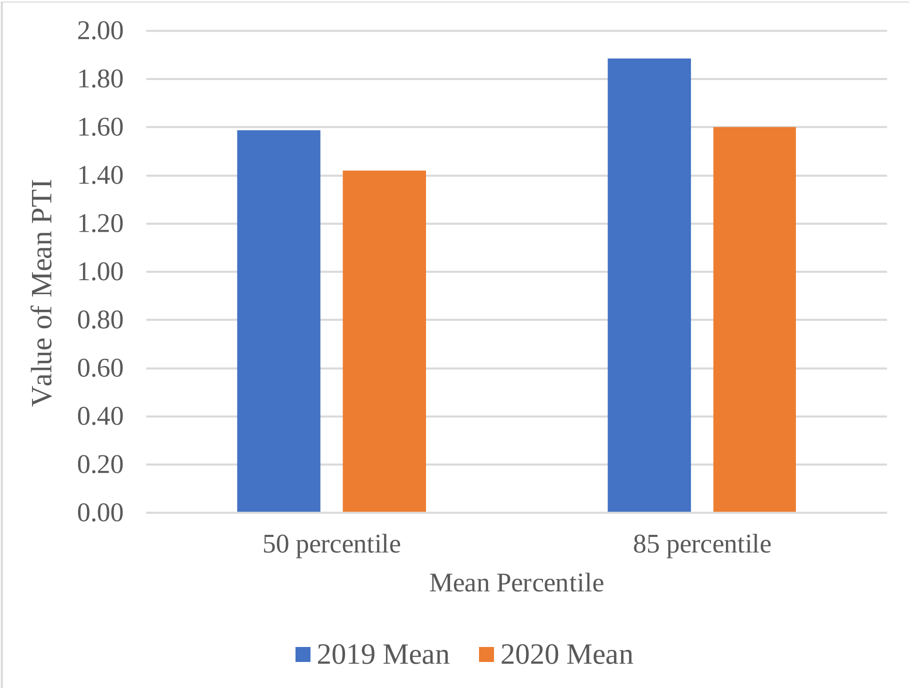




Figure 4-8 (a): Bar charts showing mean and standard deviation for TTI at the 50$^{th}$ and 85$^{th}$ percentile



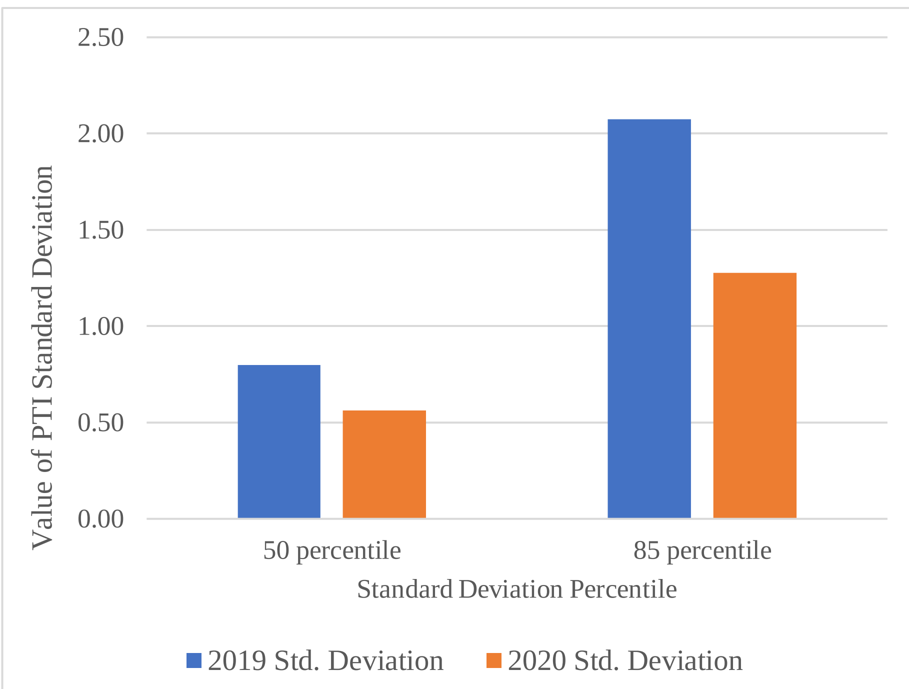
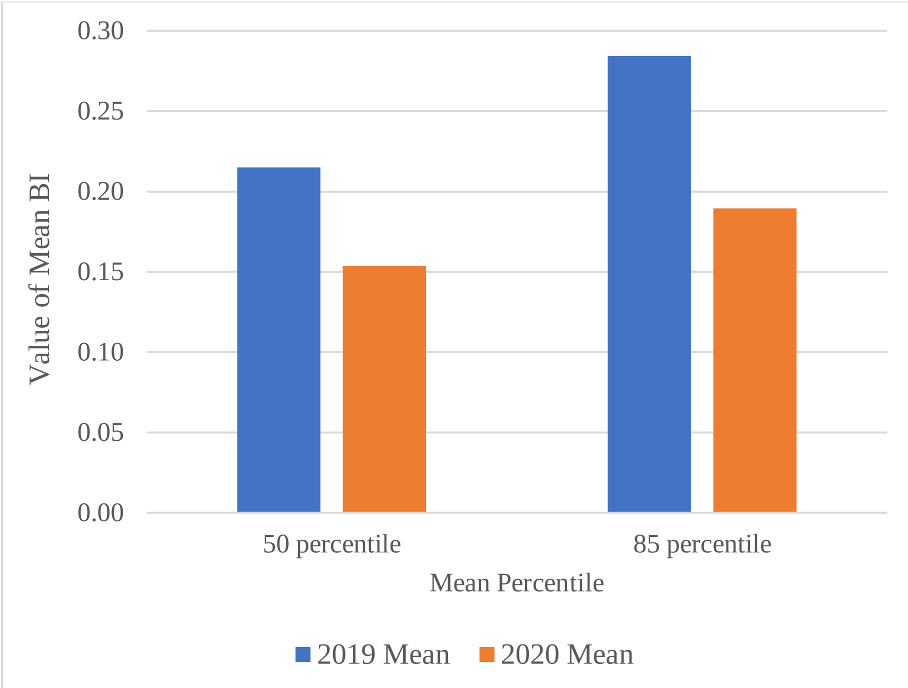




Figure 4-8 (b): Bar charts showing mean and standard deviation for PTI at the 50th and 85th percentile



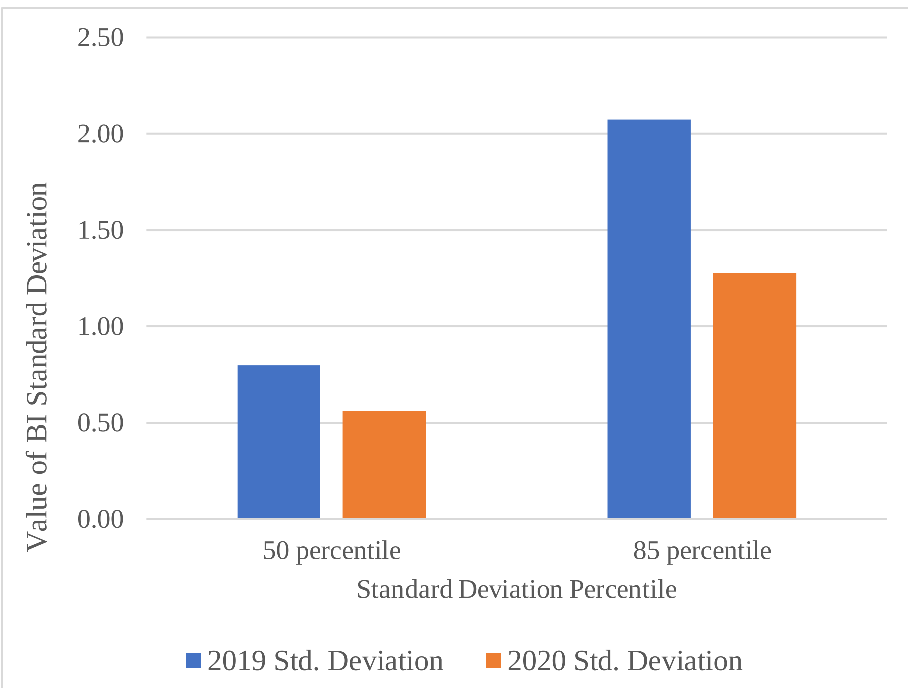




Figure 4-8 (c): Bar charts showing mean and standard deviation for BI at the 50th and 85th percentile

It is evident from Table 4-14 and Figure 4-8 that the data were positively skewed and showed a high level of kurtosis. Positive high values of kurtosis (> 3) indicate that a probability distribution is peaked and possesses thick tails. A high number of values are located around the tails of the distribution rather than around the mean.

The $50^{th}$ and $85^{th}$ percentile mean and standard deviation values provide information about the central tendency and variability of the data respectively. The $85^{th}$ percentile values can be considered a better representation of actual conditions for all roads as roads tend to show a high degree of randomness in relation to mobility. Using the $85^{th}$ percentile values can give a better representation of real-life conditions (Martinelli et al., 2023).

Owing to the high level of skewness and kurtosis observed for the freight fluidity measures, the analysis was conducted at a more disaggregated level. The Region of Peel has 26 wards in total with 11 wards in Mississauga, 10 wards in Brampton and 5 wards in Caledon. Figure 4-9 shows the wards in each municipality.

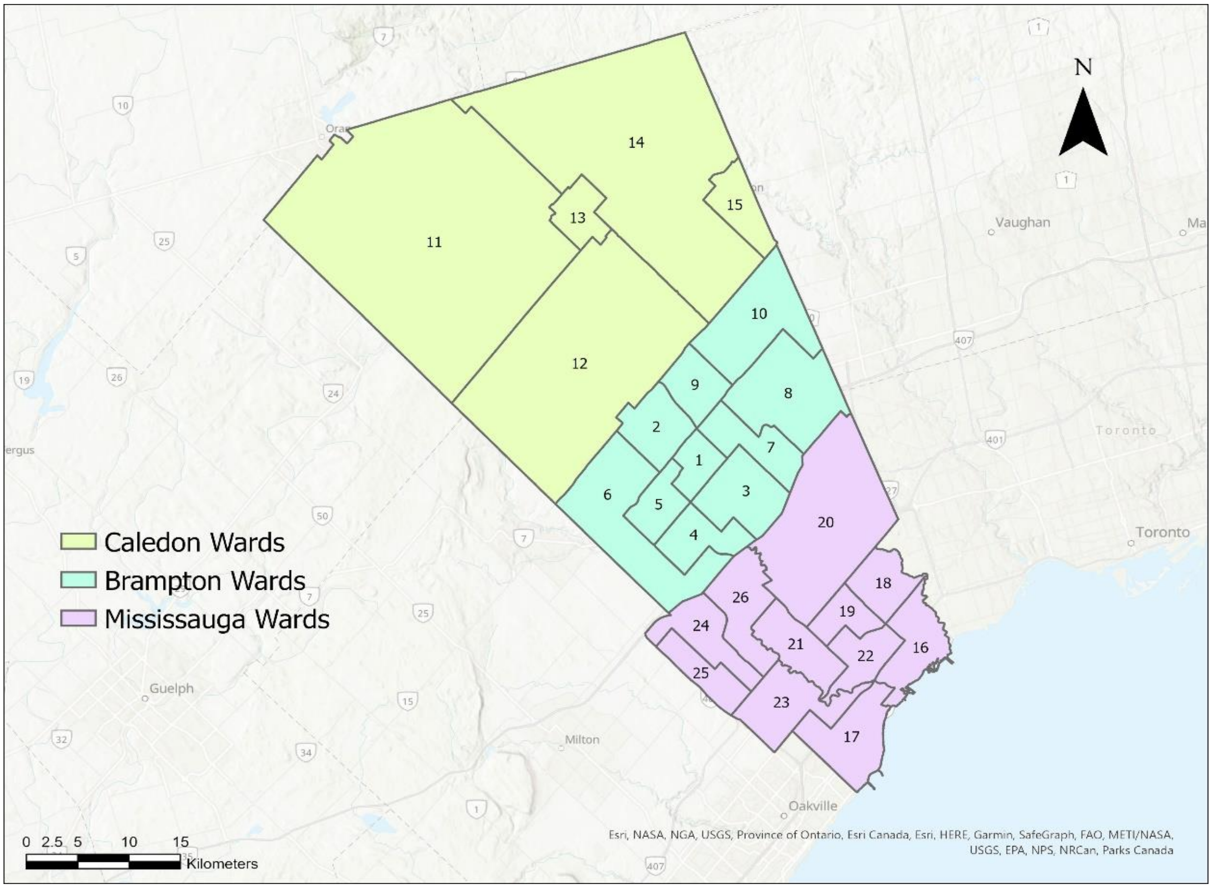



Figure 4-9: Wards in Region of Peel by municipality

The freight fluidity measures were evaluated for each ward to obtain a better insight into mobility and congestion in each municipality. The ward level analysis provided information about anomalies or disparities that might be obscured when examining the data at the municipal or regional level. Disaggregated data analysis, such as this ward level analysis of freight fluidity measures, can help decision makers obtain better clarity and understanding of the characteristics, problems and needs of a particular location. This can in turn enable decision makers to make evidence-based decisions that are more likely to lead to positive outcomes and judicious use of public resources. Table 4-15 provides a breakdown of collisions and freight fluidity measures by ward in 2019 and 2020.

Table 4-15 (a): Collisions and freight fluidity measures by ward in 2019

| Ward | Municipality | TTI | PTI | BI | Collisions |
|---|---|---|---|---|---|
| 1 | Brampton | 1.34 | 2.50 | 0.66 | 7 |
| 2 | Brampton | 1.51 | 2.21 | 0.59 | 1 |
| 3 | Brampton | 1.35 | 2.85 | 0.96 | 16 |
| 4 | Brampton | 1.25 | 1.56 | 0.20 | 4 |
| 5 | Brampton | 1.26 | 1.69 | 0.24 | 8 |
| 6 | Brampton | 1.31 | 2.00 | 0.37 | 15 |
| 7 | Brampton | 1.28 | 2.43 | 0.72 | 8 |
| 8 | Brampton | 1.29 | 2.23 | 0.57 | 48 |
| 9 | Brampton | 1.45 | 2.10 | 0.33 | 12 |
| 10 | Brampton | 1.26 | 2.18 | 0.60 | 6 |
| 11 | Caledon | 1.23 | 1.68 | 0.31 | 2 |
| 12 | Caledon | 1.14 | 1.62 | 0.29 | 11 |
| 13 | Caledon | 1.06 | 1.32 | 0.18 | 1 |
| 14 | Caledon | 1.19 | 1.62 | 0.23 | 9 |
| 15 | Caledon | 1.16 | 1.55 | 0.28 | 32 |
| 16 | Mississauga | 1.23 | 1.75 | 0.32 | 14 |
| 17 | Mississauga | 1.20 | 1.54 | 0.21 | 6 |
| 18 | Mississauga | 1.24 | 1.83 | 0.39 | 3 |
| 19 | Mississauga | 1.29 | 1.54 | 0.14 | 4 |
| 20 | Mississauga | 1.25 | 2.68 | 0.98 | 96 |
| 21 | Mississauga | 1.12 | 1.34 | 0.44 | 0 |
| 22 | Mississauga | 1.20 | 1.47 | 0.14 | 2 |
| 23 | Mississauga | 1.33 | 1.86 | 0.26 | 5 |
| 24 | Mississauga | 1.40 | 2.27 | 0.51 | 5 |
| 25 | Mississauga | 1.50 | 1.89 | 1.34 | 0 |
| 26 | Mississauga | 1.24 | 2.00 | 0.43 | 17 |

Table 4-15 (b): Collisions and freight fluidity measures by ward in 2020

| Ward | Municipality | TTI | PTI | BI | Collisions |
|---|---|---|---|---|---|
| 1 | Brampton | 1.34 | 3.49 | 1.21 | 11 |
| 2 | Brampton | 1.45 | 1.81 | 0.26 | 3 |
| 3 | Brampton | 1.36 | 2.83 | 0.89 | 40 |
| 4 | Brampton | 1.00 | 1.00 | 0.00 | 0 |
| 5 | Brampton | 1.39 | 2.25 | 0.54 | 6 |
| 6 | Brampton | 1.17 | 1.44 | 0.20 | 10 |
| 7 | Brampton | 1.27 | 2.22 | 0.58 | 18 |
| 8 | Brampton | 1.28 | 2.20 | 0.55 | 39 |
| 9 | Brampton | 1.43 | 1.81 | 0.23 | 2 |
| 10 | Brampton | 1.26 | 2.52 | 0.80 | 7 |
| 11 | Caledon | 1.02 | 1.03 | 0.01 | 2 |
| 12 | Caledon | 1.31 | 2.15 | 0.51 | 9 |
| 13 | Caledon | 1.10 | 1.19 | 0.05 | 1 |
| 14 | Caledon | 1.17 | 1.69 | 0.31 | 11 |
| 15 | Caledon | 1.19 | 1.74 | 0.38 | 2 |
| 16 | Mississauga | 1.27 | 1.81 | 0.31 | 5 |
| 17 | Mississauga | 1.29 | 1.70 | 0.35 | 0 |
| 18 | Mississauga | 1.08 | 1.21 | 0.09 | 1 |
| 19 | Mississauga | 1.33 | 1.72 | 0.24 | 0 |
| 20 | Mississauga | 1.23 | 2.62 | 0.94 | 64 |
| 21 | Mississauga | 1.27 | 1.46 | 0.09 | 2 |
| 22 | Mississauga | 1.41 | 1.93 | 0.29 | 2 |
| 23 | Mississauga | 1.38 | 2.26 | 0.44 | 1 |
| 24 | Mississauga | 1.44 | 1.98 | 0.28 | 2 |
| 25 | Mississauga | 1.54 | 1.89 | 0.40 | 0 |
| 26 | Mississauga | 1.26 | 1.74 | 0.30 | 3 |

Table 4-15 shows that Brampton wards experienced the highest congestion and mobility issues followed by Mississauga and Caledon. The wards in and around Pearson Airport showed the highest freight fluidity measures values, indicating a higher level of congestion in those areas. In addition to this, wards in Brampton that border Caledon also showed a higher level of congestion compared to other wards in Mississauga and Caledon. The warehousing and distribution facilities in and around Pearson Airport combined with the narrow arterial roads around north Brampton make wards 2 and 9 congested and resulted in high freight fluidity measure values. These findings agree with those of the *2019 Region of Peel Goods Movement Report* which identified Toronto Pearson International Airport and the CN Brampton Intermodal Yard as the primary locations for attracting and generating truck trips in the Region of Peel (Goods Movement – Region of Peel, 2019).

The Region of Peel recognizes that traffic congestion occurs all across the Region, affecting communities and businesses. Brampton has always been an area of focus, owing to Brampton's proximity to Pearson Airport, access to Highway 401 and large amounts of land already zoned for industrial use. The current analysis confirms that Brampton has the highest freight fluidity values, indicating congestion and mobility issues. The issues are particularly prominent in areas surrounding Pearson Airport and are confirmed by the ward level analysis. The freight fluidity analysis can be used to pinpoint areas of concern.

## 4.4 Spatial relationships between Collisions and Freight Fluidity Measures

The spatial relationship between collisions and freight fluidity measures was evaluated using Moran's I for 2019 and 2020. One of the primary advantages of using Moran's I is its ability to identify patterns among neighbouring points in a dataset. This information can be used to assess whether the values close together are similar (attracting) or dissimilar (repelling) from each other (Li et. al., 2007). In simple words, Moran's I can provide a numerical value to spatial clustering: if the values in the dataset tend to cluster spatially the Moran's Index will be positive. When high values repel other high values, the Moran's Index will be negative.

The equation for Moran's I is as follows:

$$\frac{n}{\sum_{i=1}^{n}.\sum_{j=1}^{n} wij} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij(xi-\bar{x})(xj-\bar{x})}{\sum_{i=1}^{n}(xi-\bar{x})^2} \qquad \text{[Equation 13]}$$

Where:

n is the number of spatial units

$x_i$ and $x_j$ are the variables in location i and j

$\bar{x}$ is the mean of all x

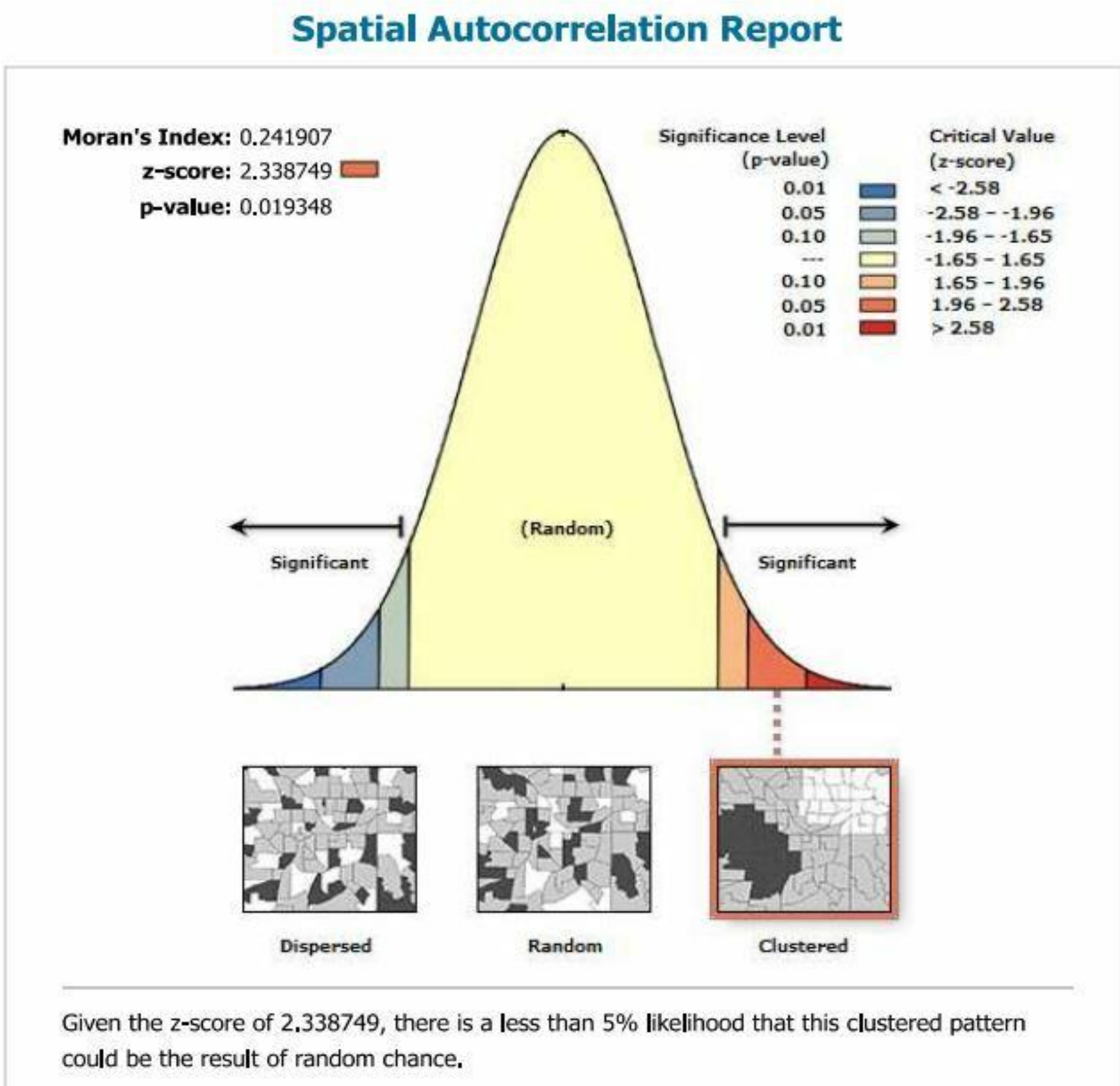
$w_{ij}$ is the binary spatial weight between i and j

Moran's Index was estimated for collisions, TTI, PTI, and BI using the Spatial Autocorrelation tool in ArcGIS Pro. The tool generates graphs where the x-axis represents the geographic area being analyzed (Region of Peel) and the y-axis represents the values of the variable under consideration (collisions, TTI, PTI and BI). The plot is divided into three regions – dispersed, random and clustered, separated by lines at x axis, indicating the level of spatial randomness.

If the data points on the diagram cluster, meaning similar values are close to each other, a positive Moran's Index is obtained with the value tending towards the clustered region on the right side of the diagram. On the other hand, for points showing dispersion, meaning dissimilar values are clustered together, a negative Moran's Index is obtained with the value tending towards the dispersed region on the left side of the diagram. After the Spatial Autocorrelation tool generates the Moran’s I value, it estimates the Expected Index value. The Expected Index value represents the average spatial autocorrelation that would be expected under the assumption of spatial randomness (values of the variable being randomly distributed across the spatial units). The Expected Index provides a baseline against which the observed Moran's I value can be compared. Based on the number of features in the dataset and the variance for the data points, the tool computes a z-score and p-value showing whether the Expected Index value is statistically different from the Moran’s I value or not.

Figure 4-10 shows an example of Moran’s I diagram showing the TTI in 2020.

*Appendix VII – Moran’s Index Analysis* shows the other Moran’s I diagrams obtained for 2019 Collisions, 2020 Collisions, 2019 TTI, 2020 TTI, 2019 PTI, 2020 PTI, 2019 BI and 2020 BI respectively.




## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.241907 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.014890 |
| **z-score:** | 2.338749 |
| **p-value:** | 0.019348 |

Figure 4-10 Moran's I analysis for 2020 TTI

A significant level of spatial clustering was observed for all the variables (collisions and freight fluidity measures) in both 2019 and 2020, with the exception being the negative Moran's I value for collisions in 2019. Table 4-16 shows the Moran's I values for 2019 and 2020 and reveals the spatial relationship between collisions and freight fluidity measures in Region of Peel.

Table 4-16: Moran's I values for collisions and freight fluidity measures in 2019 and 2020

| Year | Collision | TTI | PTI | BI |
|---|---|---|---|---|
| 2019 | -0.002224 | 0.190843 | 0.363641 | 0.291402 |
| 2020 | 0.141994 | 0.241907 | 0.165492 | 0.163654 |

For 2019, the Moran's I value for collisions was close to zero, indicating a lack of significant geospatial clustering. However, a positive Moran's Index was noted for collisions in 2020. This shift could be attributed to the noticeable reduction in truck collisions in 2020 compared to 2019, likely influenced by the approximately 8 percent decrease in truck traffic due to Covid-19 restrictions and lockdowns as reported in the "Transportation in Canada - 2020 Overview Report" (Transport Canada, 2021).

Identifying geospatial clustering is crucial for focused interventions and optimizing transportation networks. The Moran's I analysis provides valuable spatial insights, helping decision makers and stakeholders identify specific hotspots with higher collision risks and areas with inefficiencies in freight movement. This analysis aids in the development of more effective and targeted strategies for enhancing safety and mobility within the transportation system.

In summary, the Moran's Index results indicate that collisions did not show a significant geospatial correlation. Further investigations are necessary to explore potential correlation between collisions and freight fluidity measures.

## 3.5 Correlations between Collisions and Freight Fluidity Measures

The correlations between freight fluidity measures and collisions were assessed using Pearson's correlation coefficient. By examining the statistical association between these two key variables, we can gain deeper insights of how they impact the safety and mobility of transportation networks. Identifying this correlation enables the development of focused strategies that enhance both safety and mobility. Interventions that effectively reduce collisions also tend to enhance the fluidity of freight movement. By analysing correlations between collisions and freight fluidity measures, decision makers can acquire more comprehensive insights into improving traffic safety and shaping effective transportation planning strategies. Some of the advantages of finding correlation between collisions and freight fluidity measures are as follows:

1. **Identify Hotspots:** Correlation between collisions and freight fluidity measures can help identify specific high-risk locations where collisions are more likely to occur (Huang et al., 2009).

2. **Evidence-Based Predictive Modelling:** By understanding correlation between collisions and freight fluidity measures, transportation engineers can develop models that can forecast collision locations based on variations in mobility patterns (Patwary and Khattak, 2023).

3. **Optimal Resource Utilization:** Correlation between collisions and freight fluidity measures can help to predict whether spending resources on freight fluidity can help improve safety or not. This insight can help in the better allocation of resources (Zhang et al., 2017).

4. **Redundant Variables:** Analysing correlations can help identify which variables are independent and which variables show a high degree of correlation. Collecting and analysing data requires time, money and effort. Correlations can help decide which variables to analyse (Penn State, 2021).

Pearson's correlation is a statistical method used for determining a correlation coefficient between two variables. The range of Pearson's coefficient (r) is from -1 to 1, where:

1. r = 1 represents perfectly positive linear correlation
2. r = -1 represents perfectly negative linear correlation
3. r = 0 represents absolutely no linear correlation.

The degree of association estimated by Pearson's coefficient can be used to assess the strength and direction of relationship between two variables. Pearson's correlation is one of the most widely used correlation techniques in statistics and is well recognized by researchers and decision makers across the field of transportation engineering (Gamel et al., 2023). The formula for calculating Pearson's coefficient (r) is given by the following equation:

$$r = \frac{\Sigma(xi - \bar{x})(yi - \bar{y})}{\sqrt{\Sigma(xi - \bar{x})^2 \Sigma(yi - \bar{y})^2}} \qquad \text{[Equation 14]}$$

Where:

r is the Pearson's correlation coefficient

xi is the value of variable x

$\bar{x}$ is the mean of all values of variable x

$\bar{y}$ is the value of variable y

yi is the mean of all values of variable y

Table 4-17 shows the results of the Pearson's correlation analysis of collisions and freight fluidity measures for 2019 and 2020.

Table 4-17 (a): Pearson's correlation for collisions and freight fluidity measures in 2019

| | | TTI 2019 | PTI 2019 | BI 2019 | Collisions 2019 |
|---|---|---|---|---|---|
| TTI 2019 | Pearson Correlation | 1 | 0.866** | 0.518** | 0.166 |
| | Sig. (2-tailed) | | 0.000 | 0.007 | 0.418 |
| | N | 26 | 26 | 26 | 26 |
| PTI 2019 | Pearson Correlation | 0.866** | 1 | 0.867** | 0.406* |
| | Sig. (2-tailed) | 0.000 | | 0.000 | 0.040 |
| | N | 26 | 26 | 26 | 26 |
| BI 2019 | Pearson Correlation | 0.518** | 0.867** | 1 | 0.557** |
| | Sig. (2-tailed) | 0.007 | 0.000 | | 0.003 |
| | N | 26 | 26 | 26 | 26 |
| Collisions 2019 | Pearson Correlation | 0.166 | 0.406* | 0.557** | 1 |
| | Sig. (2-tailed) | 0.418 | 0.040 | 0.003 | |
| | N | 26 | 26 | 26 | 26 |
| ** Correlation is significant at the 0.01 level (2-tailed) | | | | | |
| * Correlation is significant at the 0.05 level (2-tailed) | | | | | |

Table 4-17 (b): Pearson's correlation for collisions and freight fluidity measures in 2020

| | | TTI 2020 | PTI 2020 | BI 2020 | Collisions 2020 |
|---|---|---|---|---|---|
| TTI 2020 | Pearson Correlation | 1 | 0.788** | 0.445* | 0.185 |
| | Sig. (2-tailed) | | 0.000 | 0.023 | 0.365 |
| | N | 26 | 26 | 26 | 26 |
| PTI 2020 | Pearson Correlation | 0.788** | 1 | 0.897** | 0.493* |
| | Sig. (2-tailed) | 0.000 | | 0.000 | 0.010 |
| | N | 26 | 26 | 26 | 26 |
| BI 2020 | Pearson Correlation | 0.445* | 0.897** | 1 | 0.640** |
| | Sig. (2-tailed) | 0.023 | 0.000 | | 0.000 |
| | N | 26 | 26 | 26 | 26 |
| Collisions 2020 | Pearson Correlation | 0.185 | 0.493* | 0.640** | 1 |
| | Sig. (2-tailed) | 0.365 | 0.010 | 0.000 | |
| | N | 26 | 26 | 26 | 26 |
| ** Correlation is significant at the 0.01 level (2-tailed) | | | | | |
| * Correlation is significant at the 0.05 level (2-tailed) | | | | | |

**Purpose 3:** To study the correlation between collisions and freight fluidity measures.

**Null Hypothesis (H0):** There is a no significant correlation between collisions and freight fluidity measures.

**Alternative Hypothesis (H1):** There is a significant correlation between collisions and freight fluidity measures.

**Inference:** The null hypothesis applied to the correlation between TTI and collisions, but was rejected for the correlation between PTI and collisions and for the correlation between BI and collisions. There was a statistically significant correlation between PTI and collisions and between BI and collisions for both 2019 and 2020. However, the correlation between TTI and collisions was not statistically significant for both 2019 and 2020.

**Purpose 4:** To study the correlations between TTI, PTI and BI.

**Null Hypothesis (H0):** There is a no significant correlation among the freight fluidity measures.

**Alternative Hypothesis (H1):** There is a significant correlation among the freight fluidity measures.

**Inference:** The null hypothesis was rejected as there was a statistically significant correlation among the freight fluidity measures for both 2019 and 2020.

Analysis of Variance (ANOVA) is a statistical method used to compare variances across means among three or more groups. It is employed to determine whether the means are significantly different from each other among a group of variables. ANOVA differs from t- tests and was more appropriate for this research. ANOVA can be used to compare three or more groups while t-tests are only useful for comparing two groups at one time (Molugaram, 2017).

In our case, three municipalities were to be analysed and therefore this study used ANOVA to gain an insight into whether freight fluidity measures or collisions are significantly different in the three municipalities within the Region of Peel.

Mathematically, ANOVA is expressed as follows (StatsDirect, 2021):

$$F = \frac{MSE}{MST} \qquad \text{[Equation 15]}$$

$$MSE = \frac{\sum_{i=1}^{k} . \sum_{j=1}^{ni} Yij^{2} - \sum_{i=1}^{k} \left(\frac{Ti^{2}}{ni}\right)}{n-k} \qquad \text{[Equation 16]}$$

$$MST = \frac{\sum_{i=1}^{k} \left(\frac{Ti^{2}}{ni}\right) - G^{2}/n}{k-1} \qquad \text{[Equation 17]}$$

Where:

F is the ANOVA coefficient

MST is the mean sum of squares due to treatments within groups

MSE is the mean sum of squares due to error

Yij is an observation

Ti is the group total

G is the sum total of all observations

ni is the number in group i

n is the total number of observations

ANOVA has several advantages:

1. **Identifying differences among groups:** There are three municipalities within the Region of Peel: Mississauga, Brampton and Caledon. ANOVA can be used to establish statistically significant differences in means between the freight fluidity or collisions based on the municipality. This facilitates the identification of the independent variable(s) that have a significant impact on a particular municipality. The ANOVA results could be particularly useful for identifying the kind of treatments or interventions required for each municipality (Field, 2013).

2. **Effective comparison methodology:** ANOVA is based on the principle of comparing means across three or more groups, and based on multiple pairwise t-tests for all possible combinations. The methodology covers all the possible permutations and combinations and can make the evaluation of group differences more controlled and robust (Tabachnick et al., 2013). Using ANOVA in this study could help to identify whether a specific municipality was associated with any statistically significant difference in collisions or freight fluidity measures.

3. **Statistical Significance:** ANOVA is based on a well-established statistical test for establishing whether the observed differences in means are occurring due to actual group differences or to random chance. This information is useful for decision makers and transportation analysts and helps them to make more well-informed inferences about the significance of their findings (Williams et al., 2010).

4. **Allocation of resources:** As ANOVA considers the variability within each group, the test provides a holistic view of group differences. This can be particularly useful for decision makers wishing to allocate limited resources more efficiently. ANOVA can help identify which variables (TTI, PTI, BI or collisions) require attention in which municipalities, and how resources could be allocated to yield the most significant and meaningful impact (Montgomery et al., 2021).

5. **Advancement in freight fluidity:** ANOVA is useful for advancing the concept of freight fluidity by helping transportation professionals to understand the significance of differences between different freight fluidity measures. This understanding contributes to the collection of new evidence and to the development of theories and inferences in the field of freight fluidity (Seo et al., 2019).

In this research, ANOVA was used as a statistical tool for comparing the means of the number of collisions and comparing the freight fluidity measures across the municipalities in the Region of Peel. Hypothesis testing was conducted to draw meaningful conclusions from the data. The p-value for the difference between the means should be less than 0.05 for the difference to be significant. The purpose of the analysis was to help contribute to the advancement of freight fluidity in respective municipalities by using the statistical significance of differences among the different freight fluidity measures (TTI, PTI, BI) and collisions.

Table 4-18 shows the results of the ANOVA analysis for collisions and freight fluidity measures for Mississauga, Brampton and Caledon in 2019 and 2020.

Table 4-18 (a): Results of the ANOVA analysis for collisions and freight fluidity measures in 2019 for Mississauga, Brampton and Caledon

| | | Sum of Squares | df | Mean Square | F | Significance |
|---|---|---|---|---|---|---|
| TTI 2019 | Between Groups | 0.452 | 2 | 0.226 | 1.901 | 0.172 |
| | Within Groups | 2.732 | 23 | 0.119 | | |
| | Total | 3.183 | 25 | | | |
| PTI 2019 | Between Groups | 2.436 | 2 | 1.218 | 3.339 | 0.053 |
| | Within Groups | 8.390 | 23 | 0.365 | | |
| | Total | 10.825 | 25 | | | |
| BI 2019 | Between Groups | 0.339 | 2 | 0.169 | 3.039 | 0.067 |
| | Within Groups | 1.282 | 23 | 0.056 | | |
| | Total | 1.621 | 25 | | | |
| Collisions 2019 | Between Groups | 28.479 | 2 | 14.240 | 0.033 | 0.968 |
| | Within Groups | 9938.136 | 23 | 432.093 | | |
| | Total | 9966.615 | 25 | | | |

Table 4-18 (b): Results of the ANOVA analysis for collisions and freight fluidity measures in 2020 for Mississauga, Brampton and Caledon

| | | Sum of Squares | df | Mean Square | F | Significance |
|---|---|---|---|---|---|---|
| TTI 2020 | Between Groups | 0.289 | 2 | 0.145 | 1.087 | 0.354 |
| | Within Groups | 3.058 | 23 | 0.133 | | |
| | Total | 3.347 | 25 | | | |
| PTI 2020 | Between Groups | 2.404 | 2 | 1.202 | 2.244 | 0.129 |
| | Within Groups | 12.317 | 23 | 0.536 | | |
| | Total | 14.721 | 25 | | | |
| BI 2020 | Between Groups | 0.419 | 2 | 0.209 | 2.298 | 0.123 |
| | Within Groups | 2.095 | 23 | 0.091 | | |
| | Total | 2.513 | 25 | | | |
| Collisions 2020 | Between Groups | 322.534 | 2 | 161.267 | 0.667 | 0.523 |
| | Within Groups | 5562.582 | 23 | 241.851 | | |
| | Total | 5885.115 | 25 | | | |

**Purpose 5:** To study the difference among the means of TTI for Mississauga, Brampton and Caledon.

**Null Hypothesis (H0):** There is a no significant difference among the means of TTI for Mississauga, Brampton and Caledon.

**Alternative Hypothesis (H1):** There is a significant difference among the means of TTI for Mississauga, Brampton and Caledon.

**Inference:** The null hypothesis was accepted for TTI for Mississauga, Brampton and Caledon in both 2019 and 2020. As no ANOVA significance value was below 0.05, there was no statistically significant difference among the TTI means for any of the municipalities.

**Purpose 6:** To study the difference among the means of PTI for Mississauga, Brampton and Caledon.

**Null Hypothesis (H0):** There is a no significant difference among the means of PTI for Mississauga, Brampton and Caledon.

**Alternative Hypothesis (H1):** There is a significant difference among the means of PTI for Mississauga, Brampton and Caledon.

**Inference:** The null hypothesis was accepted for PTI for Mississauga, Brampton and Caledon in both 2019 and 2020. As no ANOVA significance value was below 0.05, there was no statistically significant difference among the PTI means for any of the municipalities.

**Purpose 7:** To study the difference among the means of BI for Mississauga, Brampton and Caledon.

**Null Hypothesis (H0):** There is a no significant difference among the means of BI for Mississauga, Brampton and Caledon.

**Alternative Hypothesis (H1):** There is a significant difference among the means of BI for Mississauga, Brampton and Caledon.

**Inference:** The null hypothesis was accepted for BI for Mississauga, Brampton and Caledon in both 2019 and 2020. As no ANOVA significance value was below 0.05, there was no statistically significant difference among the BI means for any of the municipalities.

**Purpose 8:** To study the difference among the means for the number of collisions in Mississauga, Brampton and Caledon.

**Null Hypothesis (H0):** There is a no significant difference among the means of collisions for Mississauga, Brampton and Caledon.

**Alternative Hypothesis (H1):** There is a significant difference among the means of collisions for Mississauga, Brampton and Caledon.

**Inference:** The null hypothesis was accepted for collisions for Mississauga, Brampton and Caledon in both 2019 and 2020. As no ANOVA significance value was below 0.05, there was no statistically significant difference among the means for the number of collisions in the municipalities.

The correlations between the freight fluidity measures and the number of collisions were evaluated for Mississauga, Brampton and Caledon independently using Pearson's correlation. Table 4-19 shows the results for Pearson's correlation between collisions and freight fluidity measures for each municipality in 2019 and 2020.

Table 4-19 (a): Pearson's correlation for collisions and freight fluidity measures in Mississauga, Brampton and Caledon in 2019

| **2019** | | **TTI Mississauga** | **PTI Mississauga** | **BI Mississauga** | **Collisions Mississauga** |
|---|---|---|---|---|---|
| Collisions Mississauga | Pearson Correlation | 0.229 | 0.543 | 0.859 | 1 |
| | Sig. (2-tailed) | 0.497 | 0.084 | 0.001 | |
| | N | 11 | 11 | 11 | 11 |

| **2019** | | **TTI Brampton** | **PTI Brampton** | **BI Brampton** | **Collisions Brampton** |
|---|---|---|---|---|---|
| Collisions Brampton | Pearson Correlation | -0.174 | 0.170 | 0.143 | 1 |
| | Sig. (2-tailed) | 0.632 | 0.638 | 0.694 | |
| | N | 10 | 10 | 10 | 10 |

| **2019** | | **TTI Caledon** | **PTI Caledon** | **BI Caledon** | **Collisions Caledon** |
|---|---|---|---|---|---|
| Collisions Caledon | Pearson Correlation | 0.139 | 0.139 | 0.277 | 1 |
| | Sig. (2-tailed) | 0.824 | 0.824 | 0.652 | |
| | N | 5 | 5 | 5 | 5 |

Table 4-19 (b): Pearson's correlation for collisions and freight fluidity measures in Mississauga, Brampton and Caledon in 2020

| 2020 | | TTI Mississauga | PTI Mississauga | BI Mississauga | Collisions Mississauga |
|---|---|---|---|---|---|
| Collisions Mississauga | Pearson Correlation | 0.147 | 0.470 | 0.861 | 1 |
| | Sig. (2-tailed) | 0.666 | 0.145 | 0.001 | |
| | N | 11 | 11 | 11 | 11 |

| 2020 | | TTI Brampton | PTI Brampton | BI Brampton | Collisions Brampton |
|---|---|---|---|---|---|
| Collisions Brampton | Pearson Correlation | 0.109 | 0.415 | 0.440 | 1 |
| | Sig. (2-tailed) | 0.765 | 0.233 | 0.204 | |
| | N | 10 | 10 | 10 | 10 |

| 2020 | | TTI Caledon | PTI Caledon | BI Caledon | Collisions Caledon |
|---|---|---|---|---|---|
| Collisions Caledon | Pearson Correlation | 0.595 | 0.682 | 0.627 | 1 |
| | Sig. (2-tailed) | 0.290 | 0.205 | 0.258 | |
| | N | 5 | 5 | 5 | 5 |

The results indicate that there was a positive correlation between collisions and freight fluidity measures for each municipality for both 2019 and 2020. The PTI and BI freight fluidity measures showed a higher degree of correlation with collisions compared to TTI. This finding corresponds with the results obtained for the aggregated Region of Peel.

Mississauga showed a high degree of correlation between collisions and freight fluidity measures in 2019, whereas Caledon showed a high degree of correlation between collisions and freight fluidity measures in 2020. The reason for this can be attributed to the noticeable shift in freight traffic movements from Mississauga to Caledon during the pandemic (Marychuk, 2020). Freight transportation and logistics emerged as Caledon's largest industry sector during the pandemic with 21 percent of all businesses and 13 percent of the workforce employed in freight transportation in Caledon (Town of Caledon, 2021). This shift is reflected in the results as Caledon was observed to show a higher degree of statistical correlation between collisions and freight fluidity measures in 2020 compared to Mississauga and Brampton.

The correlations between collisions and freight fluidity measures were analyzed for each ward in the Region of Peel to obtain additional insights into the correlations. Figure 4-11 shows the correlation between collisions and freight fluidity measures by ward for 2019 and 2020.

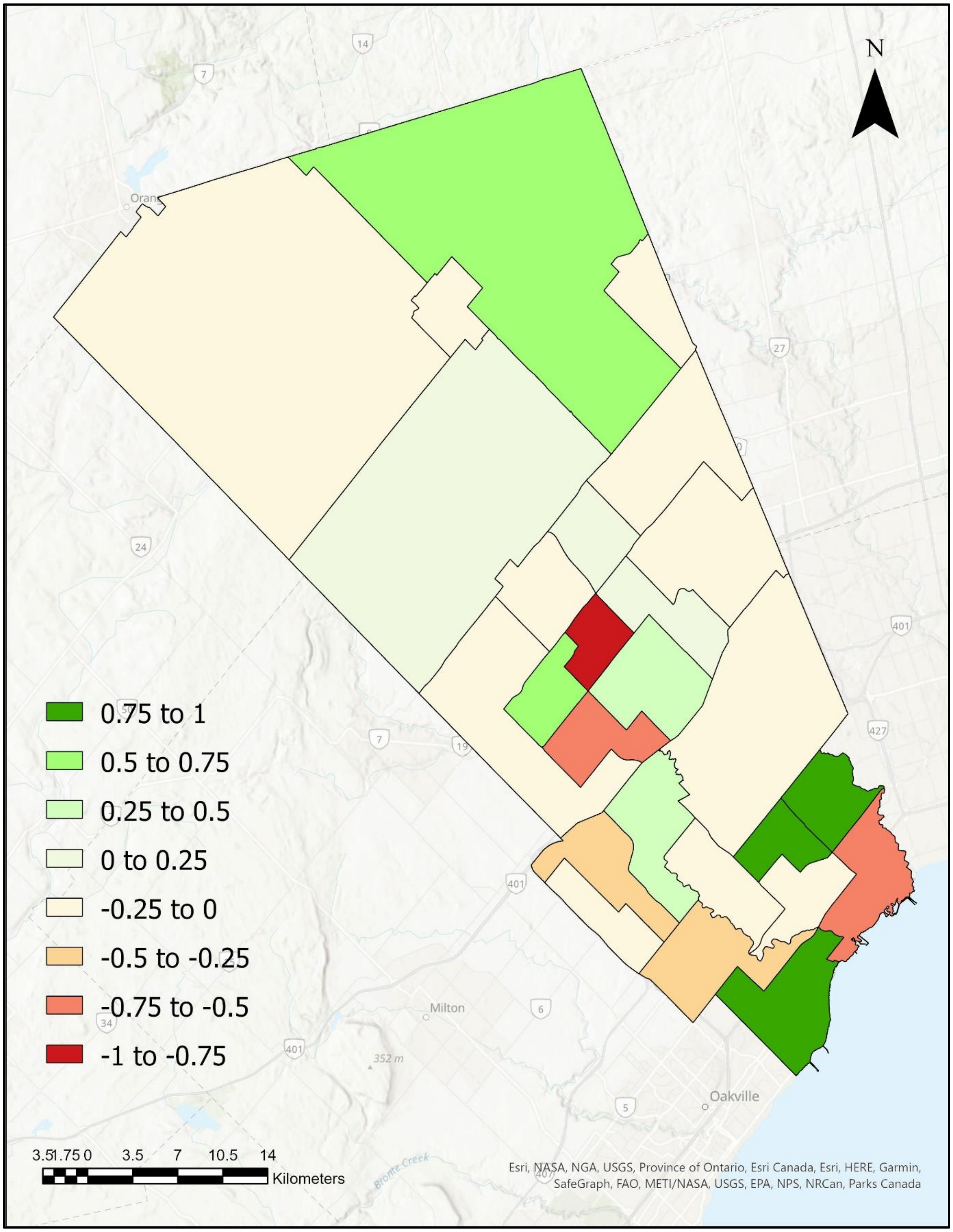



Figure 4-11 (a): Correlation between collisions and TTI in 2019

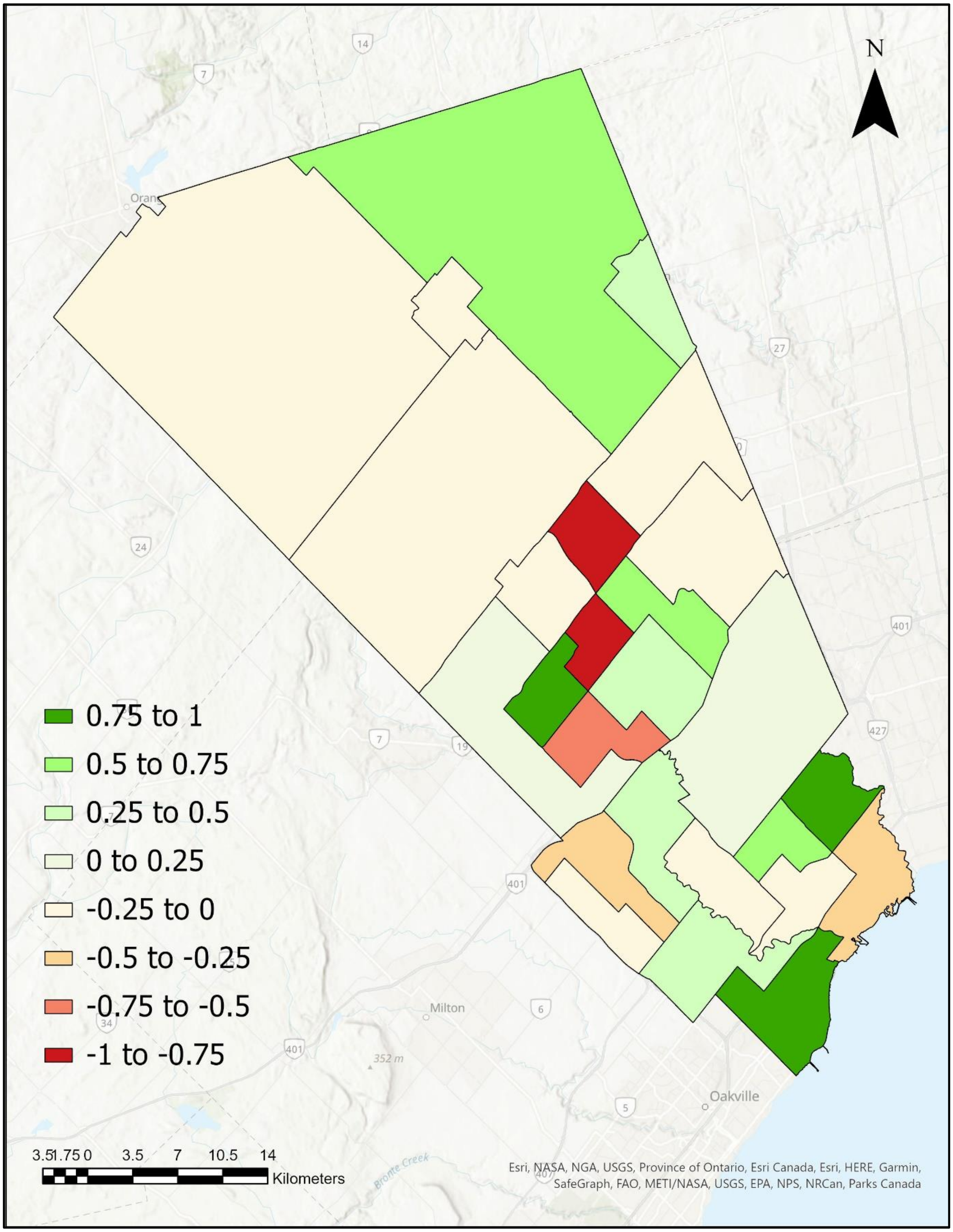



Figure 4-11 (b): Correlation between collisions and PTI in 2019

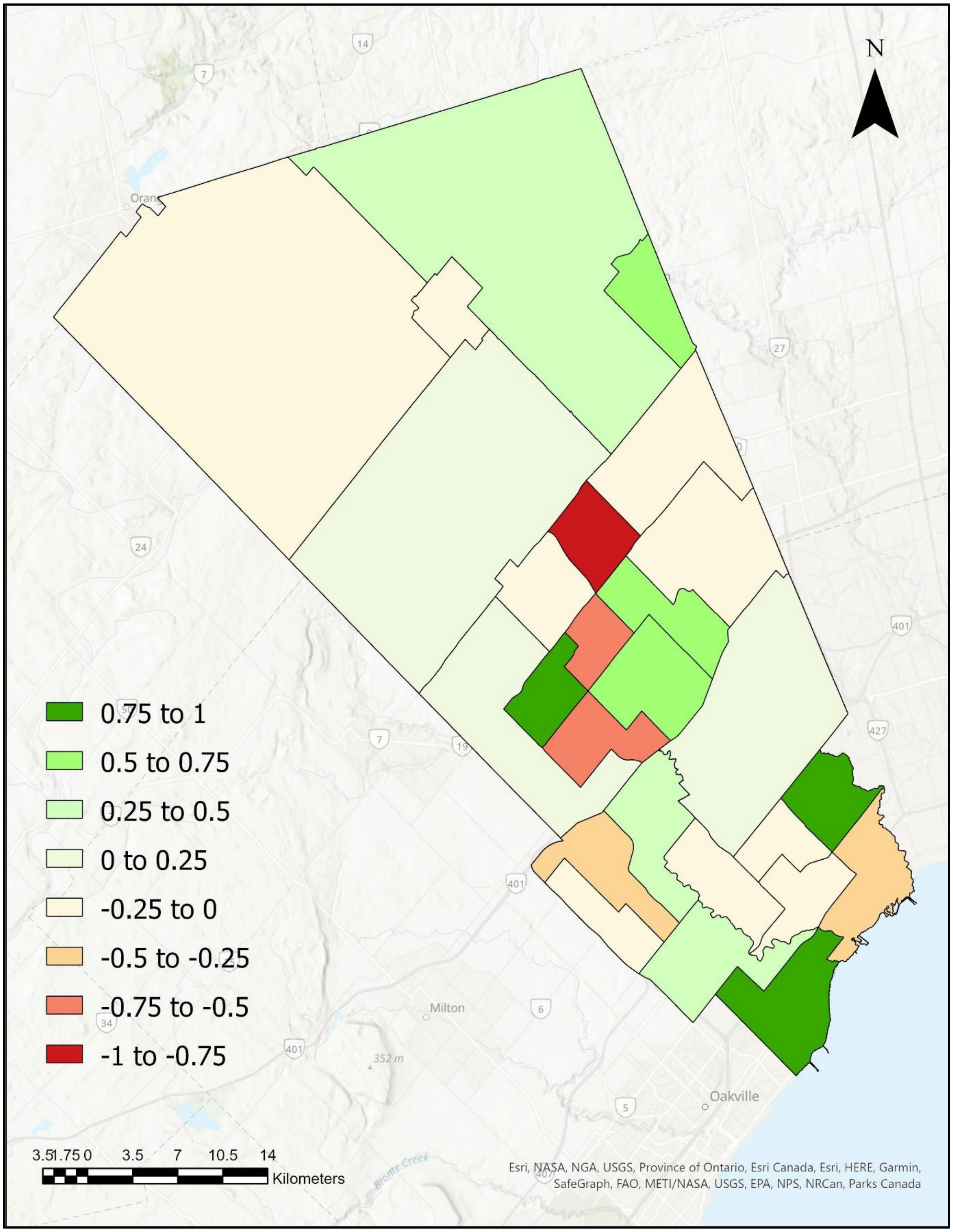



Figure 4-11 (c): Correlation between collisions and BI in 2019

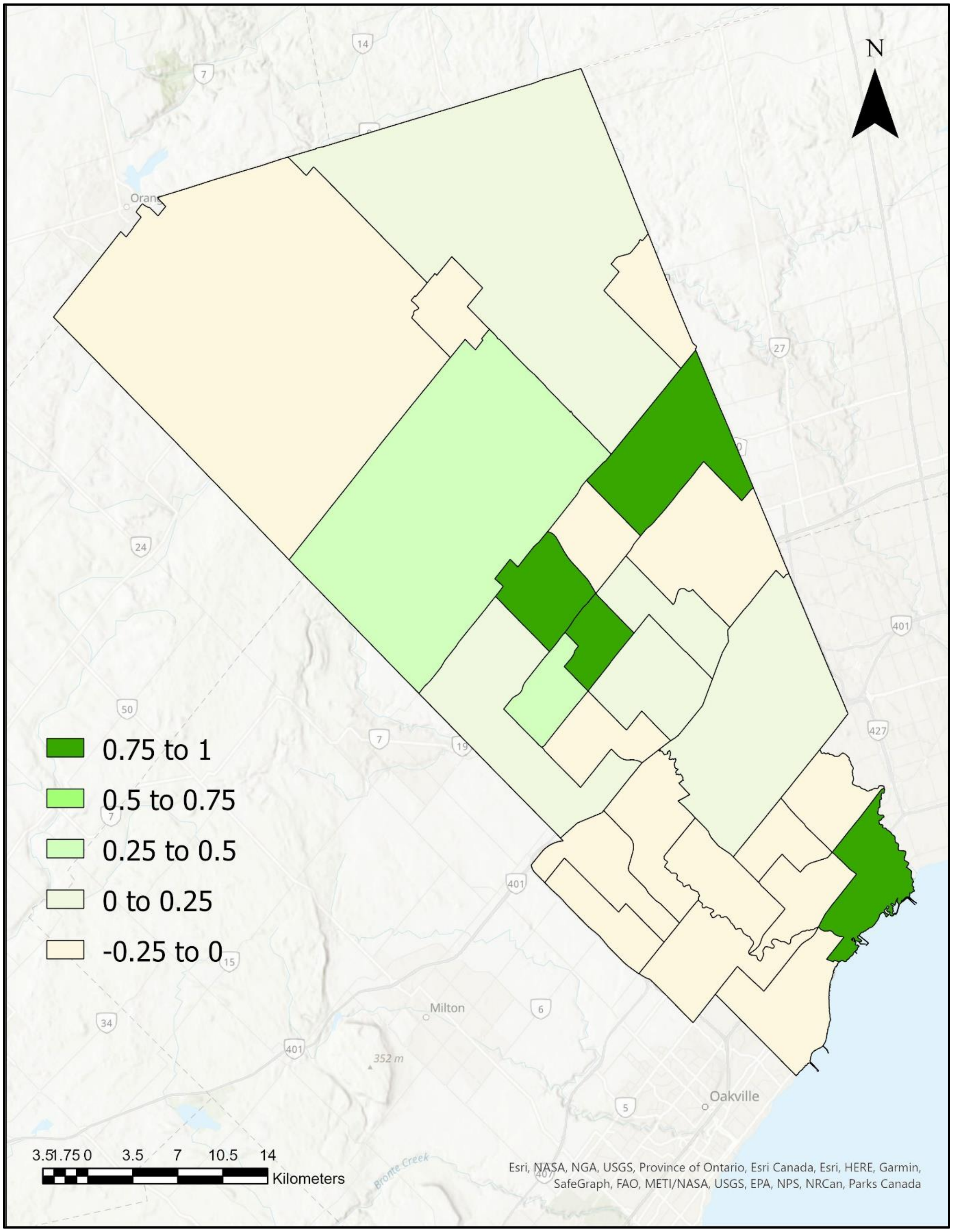



Figure 4-11 (d): Correlation between collisions and TTI in 2020

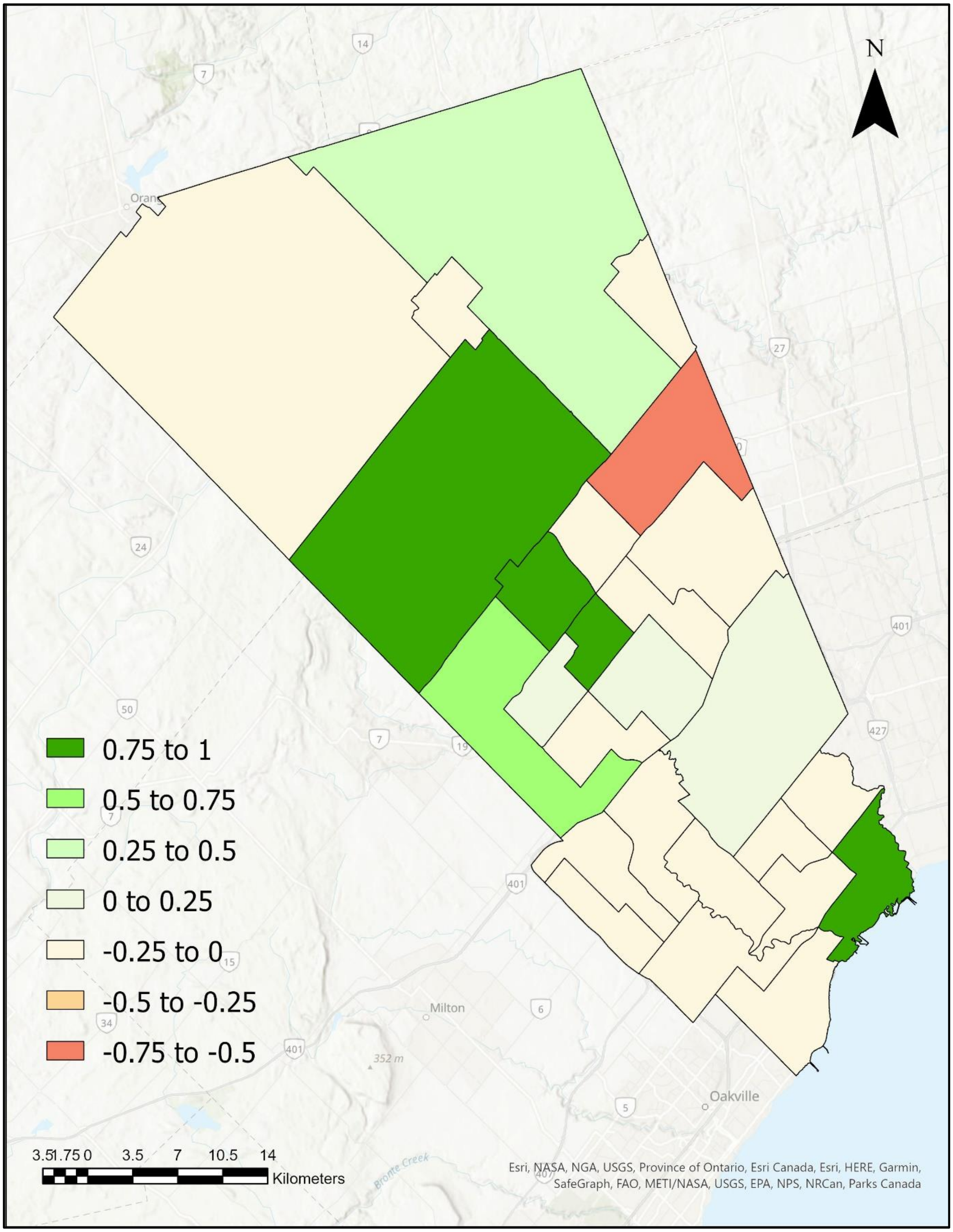



Figure 4-11 (e): Correlation between collisions and PTI in 2020

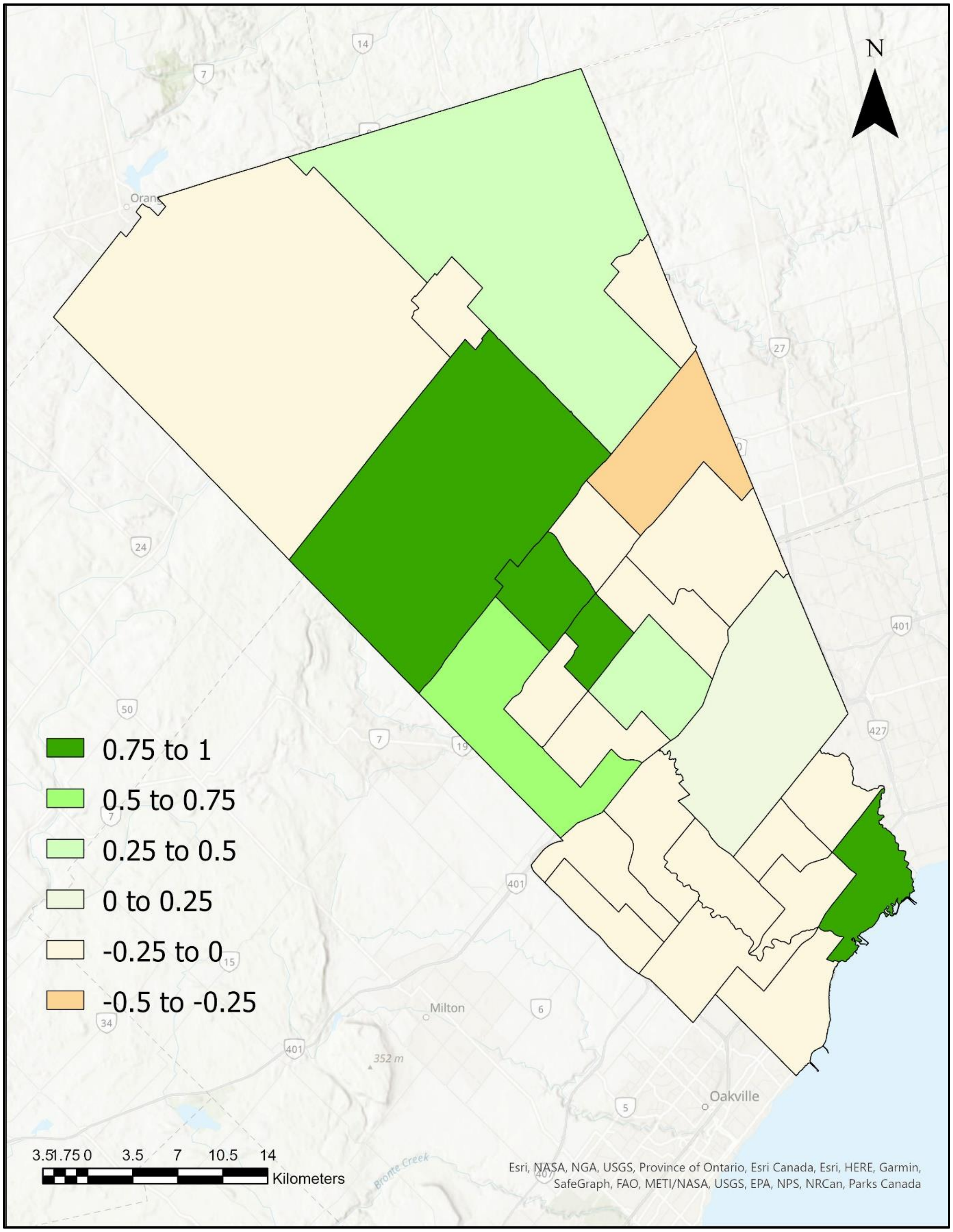



Figure 4-11 (f): Correlation between collisions and BI in 2020

It is clear from Figure 4-11 that PTI and BI showed a higher degree of correlation among wards compared to TTI. This result corresponds with the findings for the aggregated data in which the municipalities and the entire Region of Peel showed a higher level of correlation between collisions and PTI and between collisions and BI. The correlation tended towards a positive correlation for almost 80 percent of the wards. A high degree of positive correlation was observed in wards closer to Pearson Airport. This finding shows the importance of decongesting wards around Pearson Airport which in turn may help reduce collisions.

The freight fluidity and collisions analysis conducted for Region of Peel at the aggregated, municipal and ward level provided consistent outcomes. The descriptive analysis provided a detailed assessment of the collision and freight fluidity measures. The hypothesis testing helped to increase understanding of the correlations between collisions and freight fluidity measures.

The freight fluidity dashboard, in conjunction with the descriptive analysis and correlation analysis, can help the Region of Peel to extract valuable insights from their data to make better informed decisions, improve operations, enhance safety, and control costs.

# CHAPTER 5: CONCLUSIONS

The conclusions present the key findings of this research. The contribution of this study and recommendations for future work are also considered in this chapter.

## 5.1 Summary

The research presented in this thesis suggests that a multifaceted approach involving collision and mobility analysis can help enhance the safety and efficiency of freight transportation. The 'Freight Fluidity Dashboard' is a tangible outcome of the research. The dashboard provides a platform for transportation planners and decision makers to make better informed decisions and allocate resources in a more targeted manner. It is expected that this research will help delivery companies to streamline processes, operate more efficiently, and reduce costs.

The following key outcomes were obtained from this research:

1. The Freight Fluidity Dashboard provides a tangible platform for visually assessing collision and freight fluidity measures. The dashboard provides a one-stop-shop for decision makers to visually analyze the freight fluidity measures (TTI, PTI and BI) and collisions across the Region of Peel.

2. The spatial and temporal analysis conducted for freight fluidity measures in the Region of Peel found that Brampton had the highest level of congestion of the three municipalities (i.e., higher levels than Mississauga and Caledon). This can be attributed to each freight fluidity measure (TTI, PTI and BI) being higher in Brampton than in Mississauga and Caledon in both 2019 and 2020. Brampton's proximity to Pearson Airport, access to Highway 401 and large amounts of land already zoned for industrial

use make it a favourable location for freight and logistics, as reflected in the high levels of congestion.

3. The maximum congestion for trucks was observed in the afternoon period between 1:00 PM and 4:00 PM. This is in contrast with the morning and evening peak period congestion observed for cars. Trucks involved in delivering goods in urban areas tend to avoid morning and evening rush hours.

4. Truck collisions declined by 27 percent in 2020 compared to 2019. This decline can be attributed to the lockdown and the reduction in cross border trade during the pandemic. The 2-way cross border truck flow between USA and Canada declined from 10.9 million trips in 2019 to 10.1 million trips in 2020 (-8.7 percent) and the truck traffic across the Peel Region decreased by 7.8 percent.

5. Brampton and Mississauga showed a high number of truck collisions from 2018 to 2020, accounting for 46 percent (660 collisions) and 43 percent (613 collisions) of total collisions in the Region of Peel respectively.

6. Collisions were not dependent on road length. Caledon, with the highest road length (334 km), had the lowest number of collisions (56 collisions).

7. The $85^{th}$ percentile analysis for freight fluidity measures was found to be a better representation of actual traffic conditions compared to other percentile values. Roads tend to show a high degree of randomness in relation to mobility, but $85^{th}$ percentile data provides information that mimics real-life conditions (Martinelli et al., 2023).

8. The Moran's I analysis found a high level of spatial clustering for freight fluidity measures. A high level of spatial clustering indicates that similar values of freight fluidity measures tend to be geographically closer to each other. This signifies clustering among geographical areas showing high levels of congestion in the Region of Peel.

9. The area around Toronto's Pearson Airport was observed to attract a large number of freight deliveries, especially in and around the Airport Employment Zone (AEZ). A high level of congestion, reflected by high freight fluidity measure values, was observed in wards close to Pearson Airport.

10. There was a statistically significant positive correlation between collisions and PTI (correlation coefficient of 0.406 in 2019 and 0.493 in 2020) and also between collisions and BI (correlation coefficient of 0.557 in 2019 and 0.640 in 2020). The correlation between collisions and TTI was not found to be statistically significant (correlation coefficient of 0.166 in 2019 and 0.185 in 2020).

11. Mississauga had a high degree of correlation between collisions and mobility measures in 2019 (correlation coefficient of 0.229, 0.543 and 0.859 for TTI, PTI and BI respectively), whereas Caledon had a high degree of correlation between collisions and mobility measures in 2020 (correlation coefficient of 0.595, 0.682 and 0.627 for TTI, PTI and BI respectively). This finding can be attributed to the shift in freight traffic movements from Mississauga to Caledon during the pandemic. Caledon emerged as a hub for logistics during the pandemic with 21 percent of all businesses and 13 percent of the workforce employed in freight transportation (Town of Caledon, 2021).

12. A positive correlation between collisions and freight fluidity measures was found in around 80 percent of the Region's wards. A particularly high level of correlation between collisions and freight fluidity measures was observed in wards close to Pearson Airport.

Improved mobility, efficient traffic management and reduced congestion can contribute to reducing the number of collisions and enhancing overall transportation safety. Reducing the number of collisions can positively impact mobility by minimizing congestion and delays on the arterial road network. The research undertaken for this thesis assessed the relationship between collision and freight fluidity measures and helped to show that congestion in transportation networks can increase the likelihood of collisions. This research can enhance decision making for more effective and efficient transportation system in the following manner:

1. **Informed Policy Development:** Understanding the correlation between freight fluidity measures and collisions can help create targeted and evidence-based interventions to improve both safety and mobility in freight transportation networks.

2. **Improved Resource Allocation:** The Moran's I analysis can help decision makers allocate resources more effectively by pinpointing specific areas with higher collision risks or inefficiencies in freight fluidity.

3. **Optimized Infrastructure Investment:** The descriptive data analysis can be instrumental in identifying priority areas that require infrastructure investment. A better knowledge of areas experiencing congestion and collisions can help streamline the

investment process, thereby reducing collisions and enhancing the efficiency of freight movement.

4. **Responsive Traffic Management:** The freight fluidity dashboard can help implement responsive traffic management strategies. This includes rerouting, adjusting schedules, and deploying resources effectively to address unexpected delays and mitigate collision risks, contributing to a more adaptive and resilient transportation system.

This research on freight fluidity measures and collisions can help foster collaboration among stakeholders, including government agencies, transportation authorities, and private logistics entities. Evidence-based informed decision making based on this research can provide a more cohesive and coordinated approach to improving overall transportation system performance.

## 5.2 Contribution

There is limited literature that explicitly establishes a relationship between truck collision and freight fluidity measures. Despite extensive research on freight fluidity, the predominant focus of known research on freight fluidity has been on freeways, with limited analysis on arterial roads. This research endeavours to address the existing void in the literature by undertaking a comprehensive analysis of freight fluidity measures, specifically the Travel Time Index (TTI), Planning Time Index (PTI), and Buffer Index (BI), across all arterial roads within the Region of Peel.

The dashboard created in this research is a tangible outcome of the analysis, and provides a hands-on platform for the user to assess traffic conditions across any arterial road in the Region of Peel. In addition to the freight fluidity measures, the dashboard displays the geospatial location of historic collisions that took place in the Region of Peel.

This research compares and contrasts pre-pandemic freight fluidity measures and collisions with pandemic freight fluidity measures and collisions. The pandemic was generally assumed to have a significant impact on mobility trends, especially freight movements. This research provides an evidence-based outcome that shows that the pandemic did not have a significant impact on truck mobility. However, the number of collisions observed during the pandemic declined markedly as would be expected from the lockdown and reduced traffic volume. This research captured these changes and provides a tool for decision makers to use to make better informed decisions that reflect sometimes rapidly evolving travel patterns.

One of the most important contributions of this research is the spatial autocorrelation analyzed using Moran's I diagrams. The analysis showed the clustering of collisions in the Region of Peel, and also at the municipal and ward level within the region. Moran's I analysis showed the spatial clustering for freight fluidity measures, providing an evidence-based analysis of the spatial autocorrelation among freight fluidity measures (TTI, PTI and BI) respectively.

### 5.3 Future Work

The research presented in this thesis specifically focused on truck freight fluidity. However, given the multi-modal nature of fluidity, it is essential to expand this analysis to other modes of transportation. Analyzing freight fluidity across different modes would necessitate unique analytical approaches and distinct models (Eisele and Villa, 2015).

In this study, freight fluidity data were collected on an hourly basis. Utilizing finer temporal resolutions, such as 5-minute or 15-minute intervals, could offer a more detailed view of time-specific variations. While this research offers a macroscopic view of the entire Region of Peel, employing more advanced methods like weighted regression analysis on collisions and freight fluidity measures could yield deeper insights. Additionally, integrating point density analysis for identifying road segments with higher collision rates could enhance the efficacy of the Moran's I analysis. Future research could also explore using relative frequencies of collisions instead of absolute numbers.

The dashboard could provide a foundation for expanding research into the Greater Toronto Area (GTA) and subsequently the entire province of Ontario. It would also be interesting for future research to investigate changes in travel trends since the pandemic. Post-pandemic data could be investigated to study additional hypotheses and inferences.

The collision data in this study were considered in terms of location, severity and collision type. Factors such as emerging technologies, driver behaviour and vehicle characteristics could be investigated to observe their influence on truck collisions. Incorporating these factors could help freight delivery drivers to analyze the routes best suited for making deliveries. A better-informed freight delivery driver will have fewer tasks in hand, thereby reducing the possibility of collisions (Gkritza and Vachon, 2021).

In summary, this research lays a solid groundwork for decision-makers in the Region of Peel to assess and understand freight movements more thoroughly. The developed dashboard offers accessible insights for informed decision-making, aiming to enhance safety, improve mobility, and reduce costs in the transportation network.

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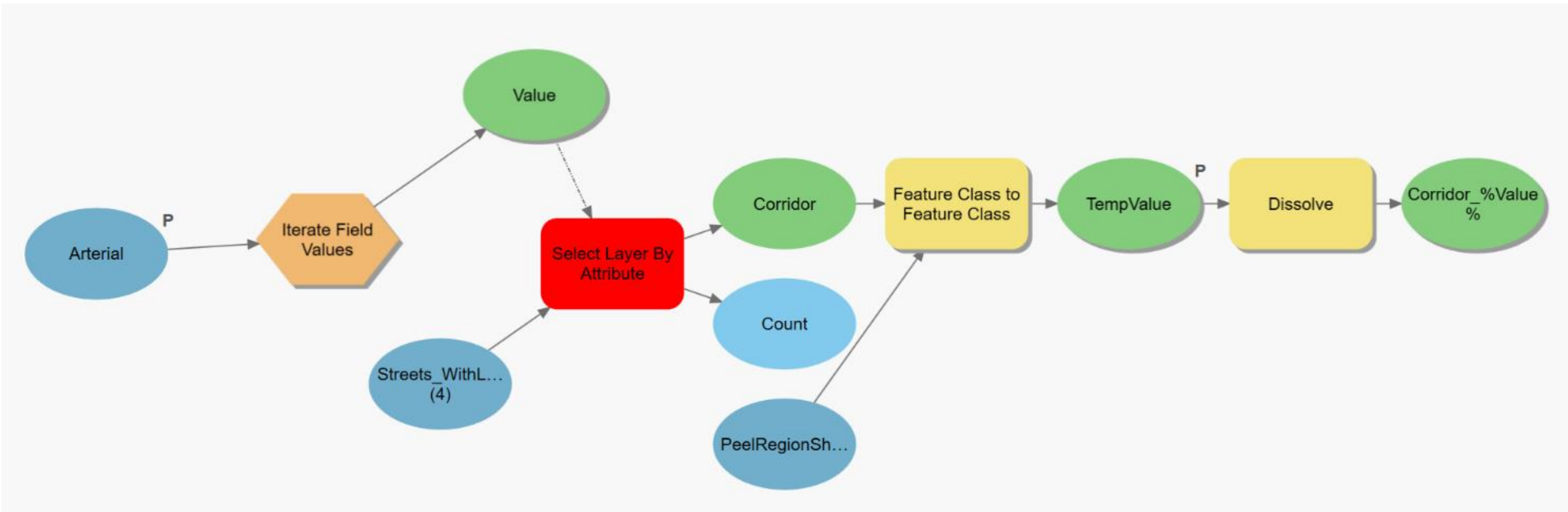
## APPENDICES

### Appendix I – ArcGIS Pro Workflow

The Workflow attributes from Collision layer and Streets layer (with freight fluidity measures) to organize and create new shapefiles for subsequent analyses.



## Appendix II – Steps to extract data from Freight Data Warehouse

a) Firstly, we need to select the link we want to analyze. Under the 'Tools' option, we use the Query function to select the links. This tool acts as a filter and allows us to select roads in the Region of Peel.

b) 'Layers' option is used for selecting the road classification (Eg- Class 5 is local roads)

c) The 'Selection' that was queried can be saved for future reference

d) The 'Range' allows us to select the date range (start date and end date), days, hours (0 to 24 hours), resolution (hourly or 15 min), vehicle type (Car or truck). If we want to analyze both Car and Truck separately, we need to send 2 requests.

e) The 'Option' allows to add columns for Freeflow speed, length of segment (in meters), standard deviation etc. The count does not give us the Volume. It's only the probe data and HERE specifically notifies not to use it as volume.

f) 'PCT' gives percentile speed (Eg- 50th percentile, 95th percentile etc)

g) The 'output format' can be JSON or csv. It is recommended to get outcome as csv as JavaScript Object Notation (JSON) is not too useful. JSON generates a JavaScript object syntax.

h) The 'Speed category' is used to extract speed in bins of say 5 km/h.

i) After we 'Submit Request', it can take a few days to get the output (depends on approval). The output will be in the form of a separate csv for each link.

j) The major roads of Peel Region consist of 7721 links. As a result, 7721 separate csv files were generated as output.

## Appendix III – Python code snippets

Python code.pdf

In [2]:
```
import glob
import pandas as pd
import numpy as np
import seaborn as sns
```

In [3]:
```
# get data file names
path =r'D:\Prateek Documents\UofT_data_Ziang\FreightDataWarehouse\ArterialR
filenames = glob.glob(path + "/*.csv")

dfs = []
for filename in filenames:
    dfs.append(pd.read_csv(filename))

# Concatenate all data into one DataFrame
big_frame = pd.concat(dfs, ignore_index=True)
```

In [4]:
```
big_frame
```

In [17]:
```
def speed_conversion(x):

    return (x * 5) + 2.5

big_frame['FifteenPercentile_Speed'] = big_frame.FifteenPercentile.apply(sp
big_frame['FifthPercentile_Speed'] = big_frame.FifthPercentile.apply(speed_


#big_frame
```

In [18]:
```
big_frame.drop(['PCT-50', 'PCT-85', 'PCT-5', 'PCT-95'], axis=1, inplace=Tru

big_frame
```

```
In [ ]: big_frame.groupby(['Time_Period'])['Mean_Speed','Freeflow_Speed', 'FifteenP
```

```
In [ ]: big_frame.groupby(['month'])['Mean_Speed','Freeflow_Speed', 'FifteenPercent
```

```
In [ ]: big_frame_segregated=big_frame.groupby(['LINK_ID','month','year','Time_Peri
```

```
In [ ]: fig, ax = plt.subplots(figsize=(30,24))
        boxplot = big_frame_hourly.boxplot(column=['TTI','PTI','BI'], by='hour' , a
```

```
In [ ]: sns.kdeplot(data = big_frame['Mean_Speed'])
```

```
In [ ]: big_frame_monthly=big_frame.groupby(['LINK_ID','month'],  as_index=False)['
```

```
In [ ]: fig, ax = plt.subplots(figsize=(30,24))
        boxplot_monthly = big_frame_monthly.boxplot(column=['TTI','PTI','BI'], by='
```

```
In [ ]: big_frame_TimePeriod=big_frame.groupby(['LINK_ID','Time_Period'],  as_index
```

```
In [ ]: fig, ax = plt.subplots(figsize=(30,24))
        boxplot_TimePeriod = big_frame_TimePeriod.boxplot(column=['TTI','PTI','BI']
```

```
In [ ]: big_frame_yearly=big_frame.groupby(['LINK_ID','year'],  as_index=False)['TT
```

```
In [ ]: fig, ax = plt.subplots(figsize=(30,24))
        boxplot_yearly = big_frame_yearly.boxplot(column=['TTI','PTI','BI'], by='ye
```

**Appendix IV – Lighting Conditions Description**

CODE 01 - Daylight

The light conditions which normally occur between one half hour after sunrise and one half hour before sunset.

CODE 02 - Daylight Artificial

The light conditions which normally occur between one half hour after sunrise and one half hour before sunset. Artificial illumination devices were functioning at the collision site.

CODE 03 - Dawn

The light conditions which normally occur between one half hour before and one half hour after sunrise.

CODE 04 - Dawn Artificial

The light conditions which normally occur between one half hour before and one half hour after sunrise. Artificial illumination devices were functioning at the collision site.

CODE 05 - Dusk

The light conditions which normally occur between one half hour before and one half hour after sunset.

CODE 06 - Dusk Artificial

The light conditions which normally occur between one half hour before and one half hour after sunset. Artificial illumination devices were functioning at the collision site.

CODE 07 - Dark

The light conditions which normally occur between one half hour after sunset and one half hour before sunrise.

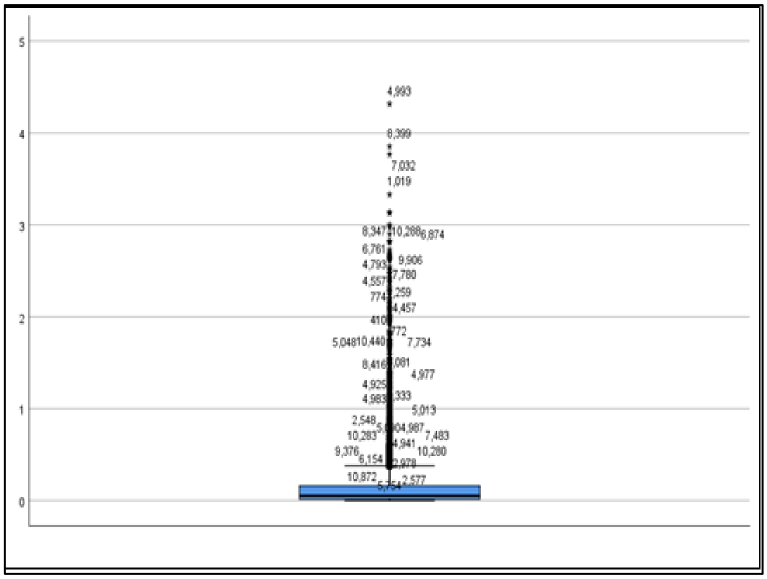
CODE 08 - Dark Artificial

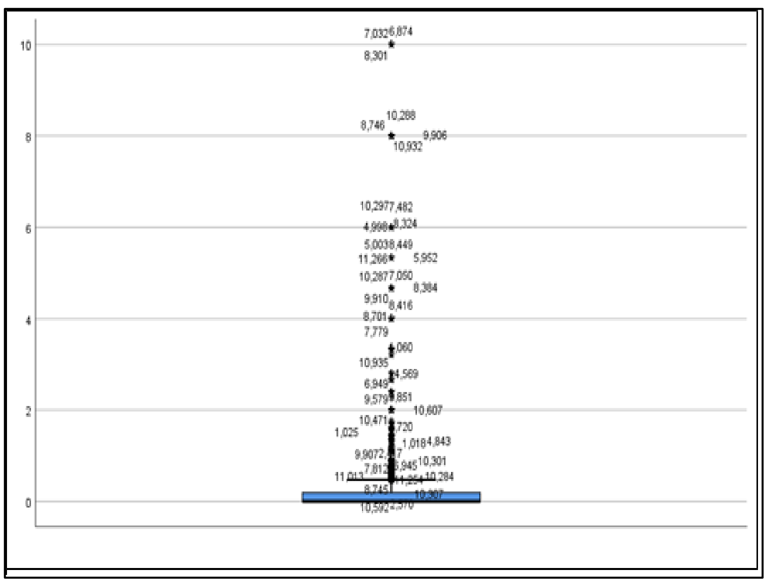
The light conditions which normally occur between one half hour after sunset and one half hour before sunrise. Artificial illumination devices were functioning at the collision site.

CODE 99 - Other

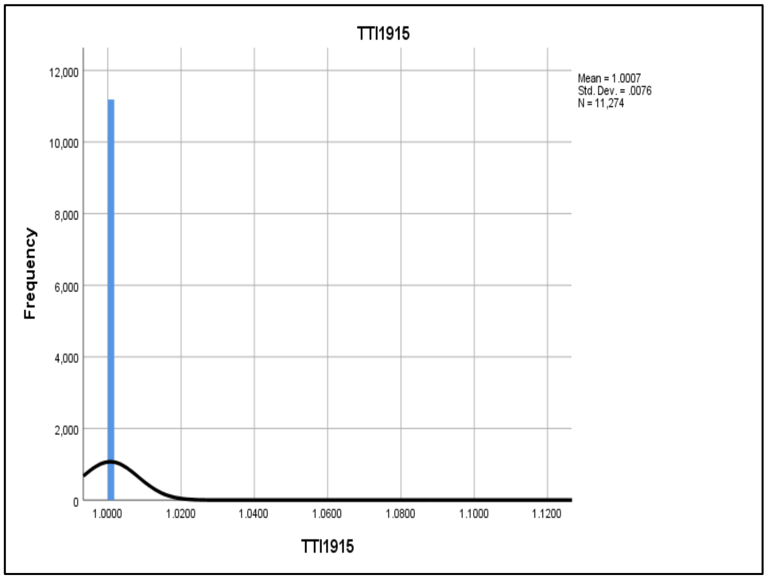
The collision occurred under light conditions not defined above. Includes non-normal occurrences such as a solar eclipse, major storm on location at which artificial illumination is not functioning.

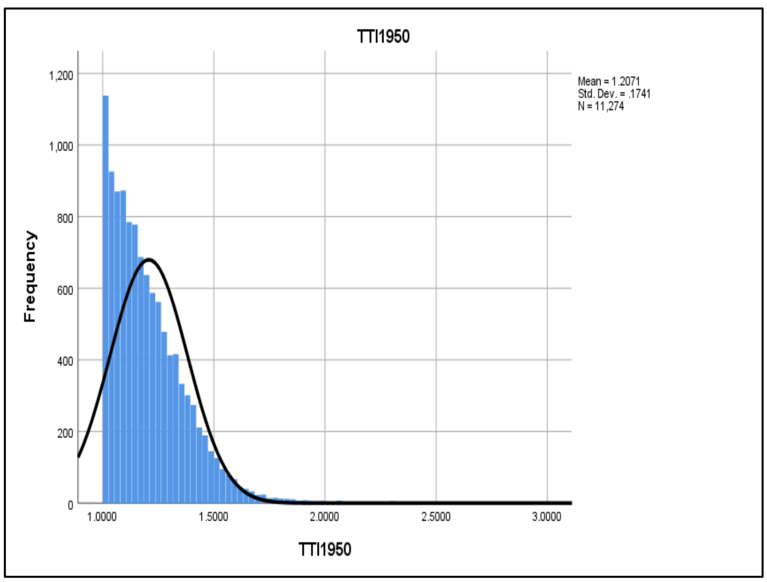
## Appendix V – Outliers for 2019 and 2020

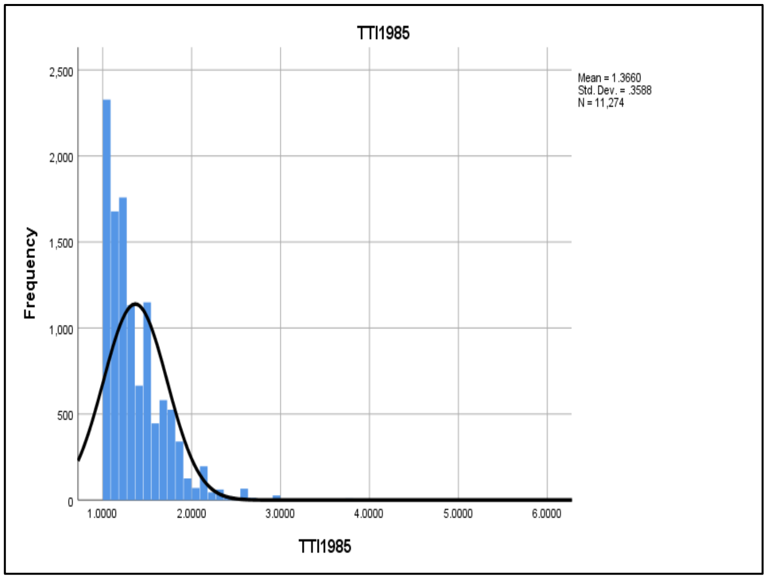


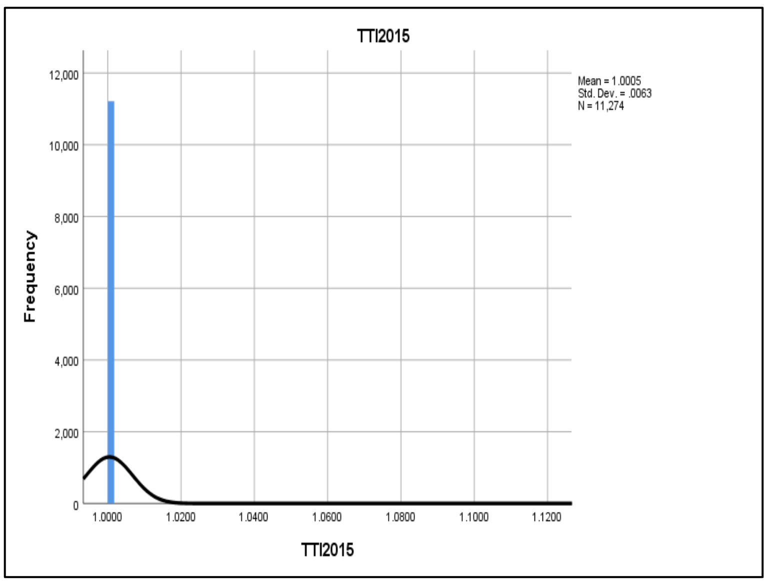


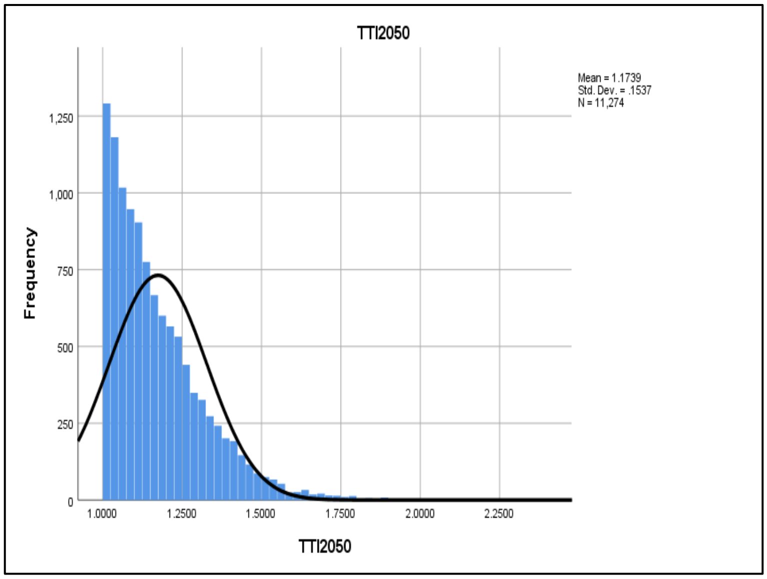
## Appendix VI – Freight Fluidity Measures Frequency Distribution for 50th percentile and 85th percentile

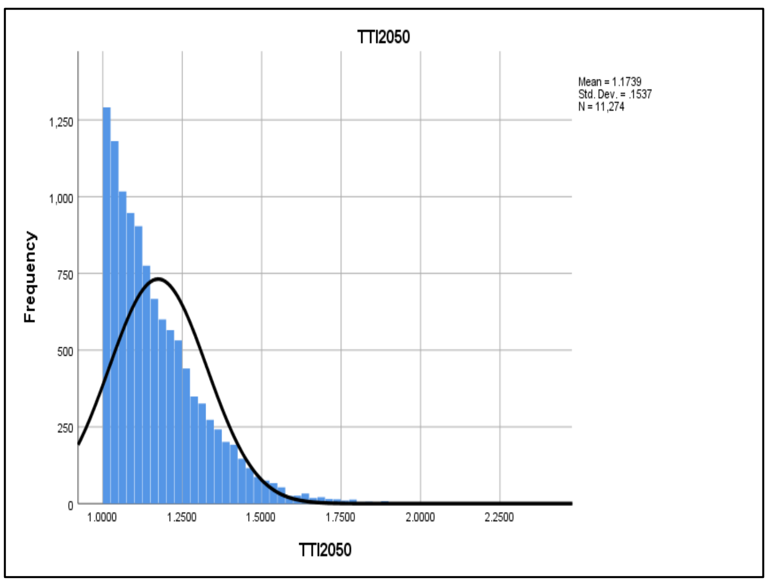


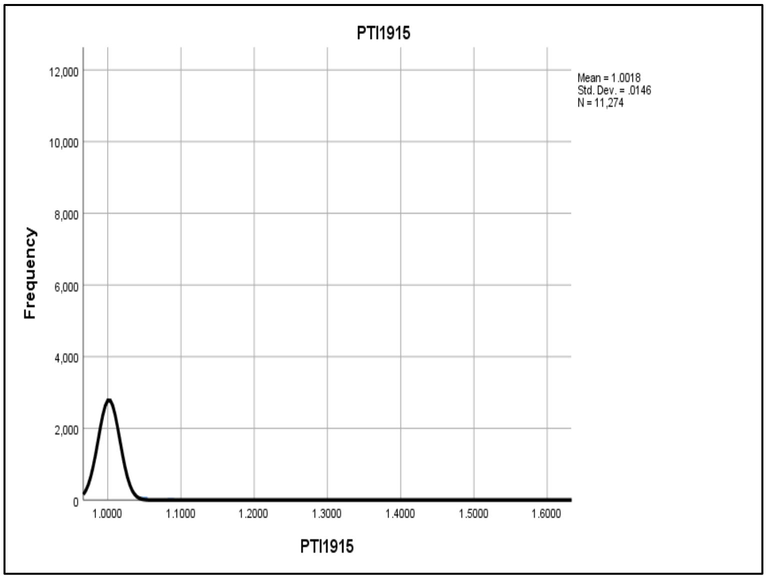



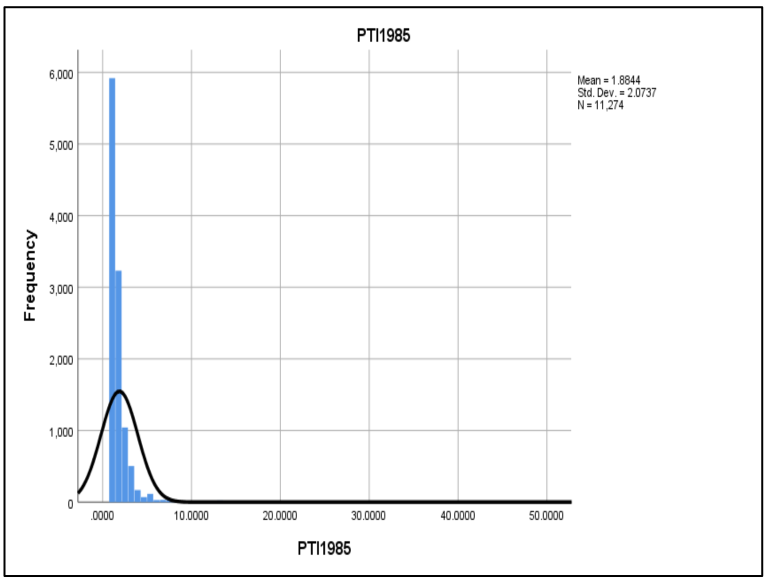

TTI1985
Mean = 1.3660
Std. Dev. = .3588
N = 11,274
Frequency
2,500
2,000
1,500
1,000
500
0
1.0000
2.0000
3.0000
4.0000
5.0000
6.0000
TTI1985

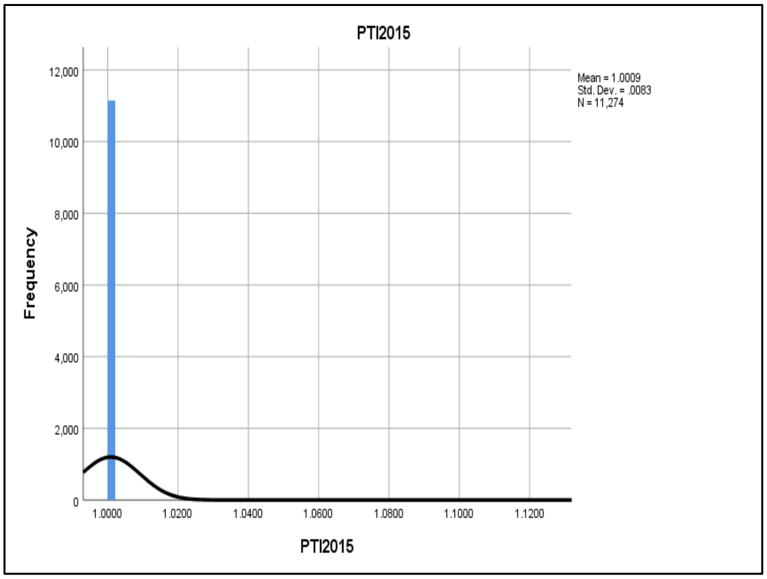

TTI2015
Mean = 1.0005
Std. Dev. = .0063
N = 11,274
Frequency
12,000
10,000
8,000
6,000
4,000
2,000
0
1.0000
1.0200
1.0400
1.0600
1.0800
1.1000
1.1200
TTI2015

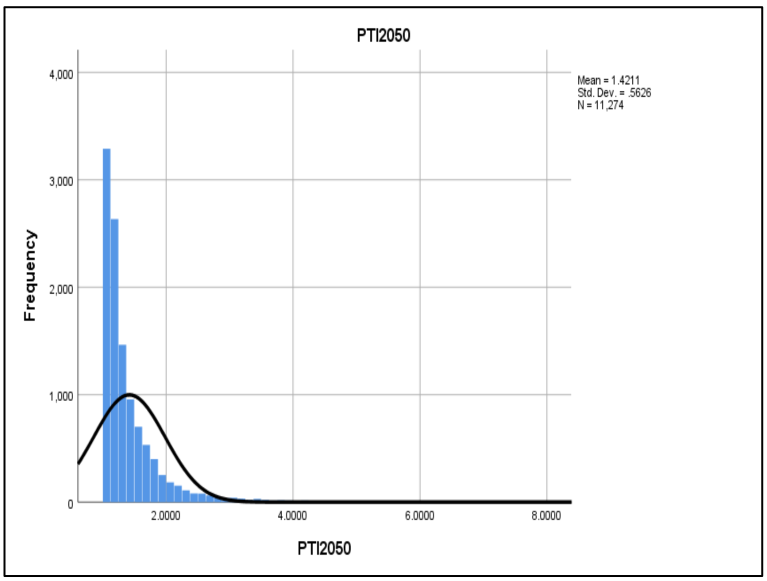

TTI2050
Mean = 1.1739
Std. Dev. = .1537
N = 11,274
Frequency
1,250
1,000
750
500
250
0
1.0000
1.2500
1.5000
1.7500
2.0000
2.2500
TTI2050

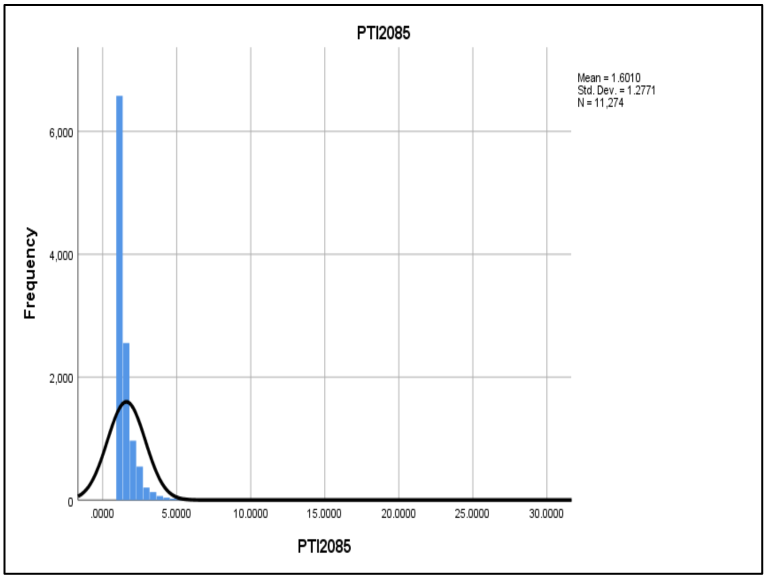

TTI2050
Mean = 1.1739
Std. Dev. = .1537
N = 11,274
Frequency
1,250
1,000
750
500
250
0
1.0000
1.2500
1.5000
1.7500
2.0000
2.2500
TTI2050

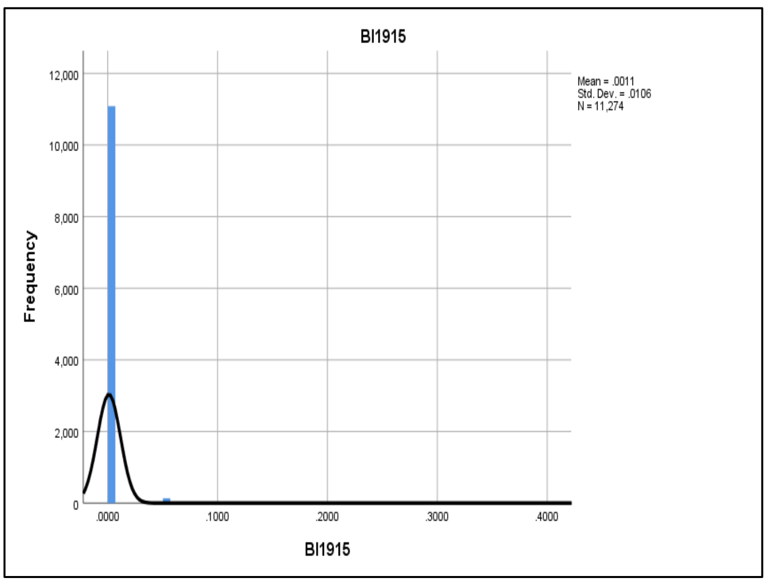

PTI1915
Mean = 1.0018
Std. Dev. = .0146
N = 11,274
Frequency
12,000
10,000
8,000
6,000
4,000
2,000
0
1.0000
1.1000
1.2000
1.3000
1.4000
1.5000
1.6000
PTI1915

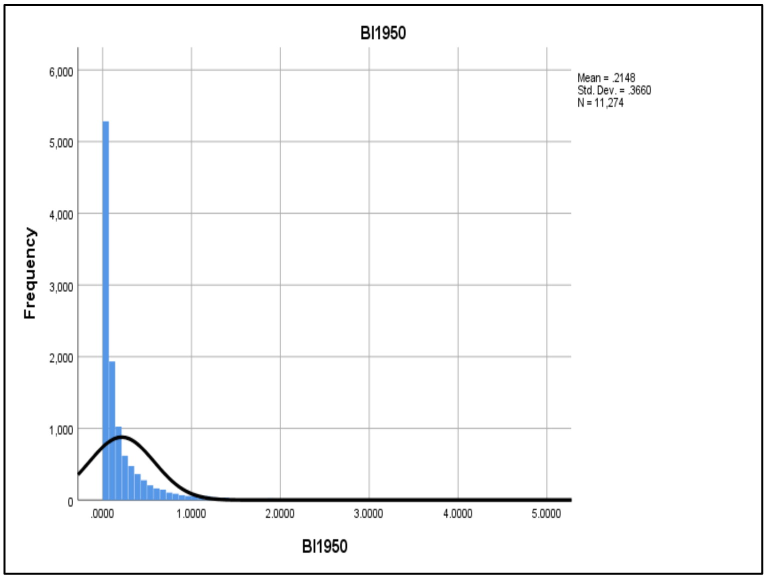

PTI1985
Mean = 1.8844
Std. Dev. = 2.0737
N = 11,274
Frequency
6,000
5,000
4,000
3,000
2,000
1,000
0
.0000
10.0000
20.0000
30.0000
40.0000
50.0000
PTI1985

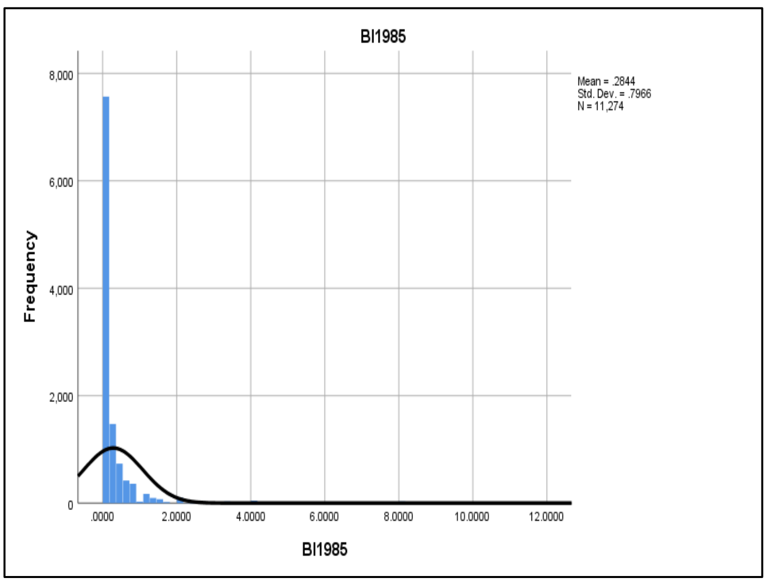

PTI2015
Mean = 1.0009
Std. Dev. = .0083
N = 11,274
Frequency
12,000
10,000
8,000
6,000
4,000
2,000
0
1.0000
1.0200
1.0400
1.0600
1.0800
1.1000
1.1200
PTI2015


PTI2050
Mean = 1.4211
Std. Dev. = .5626
N = 11,274
Frequency
4,000
3,000
2,000
1,000
0
2.0000
4.0000
6.0000
8.0000
PTI2050


PTI2085
Mean = 1.6010
Std. Dev. = 1.2771
N = 11,274
Frequency
6,000
4,000
2,000
0
.0000
5.0000
10.0000
15.0000
20.0000
25.0000
30.0000
PTI2085

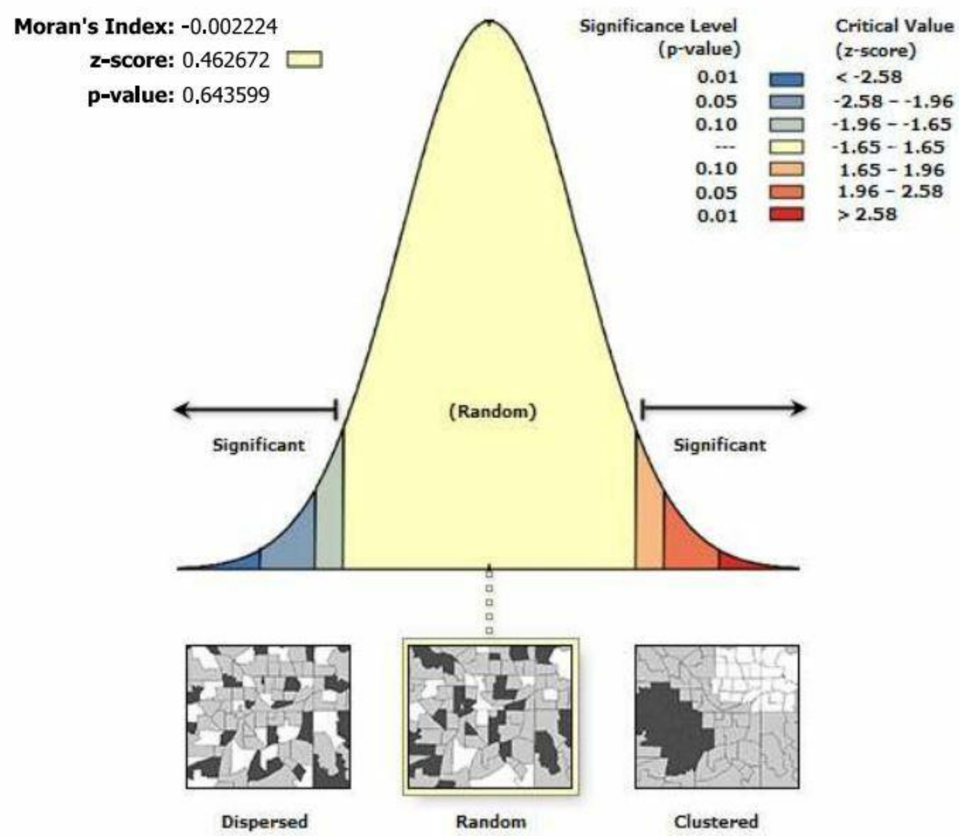

BI1915
Mean = .0011
Std. Dev. = .0106
N = 11,274
Frequency
12,000
10,000
8,000
6,000
4,000
2,000
0
.0000
.1000
.2000
.3000
.4000
BI1915


BI1950
Mean = .2148
Std. Dev. = .3660
N = 11,274
Frequency
6,000
5,000
4,000
3,000
2,000
1,000
0
.0000
1.0000
2.0000
3.0000
4.0000
5.0000
BI1950


BI1985
Mean = .2844
Std. Dev. = .7966
N = 11,274
Frequency
8,000
6,000
4,000
2,000
0
.0000
2.0000
4.0000
6.0000
8.0000
10.0000
12.0000
BI1985

## Appendix VII – Moran’s Index Analysis

### Spatial Autocorrelation Report



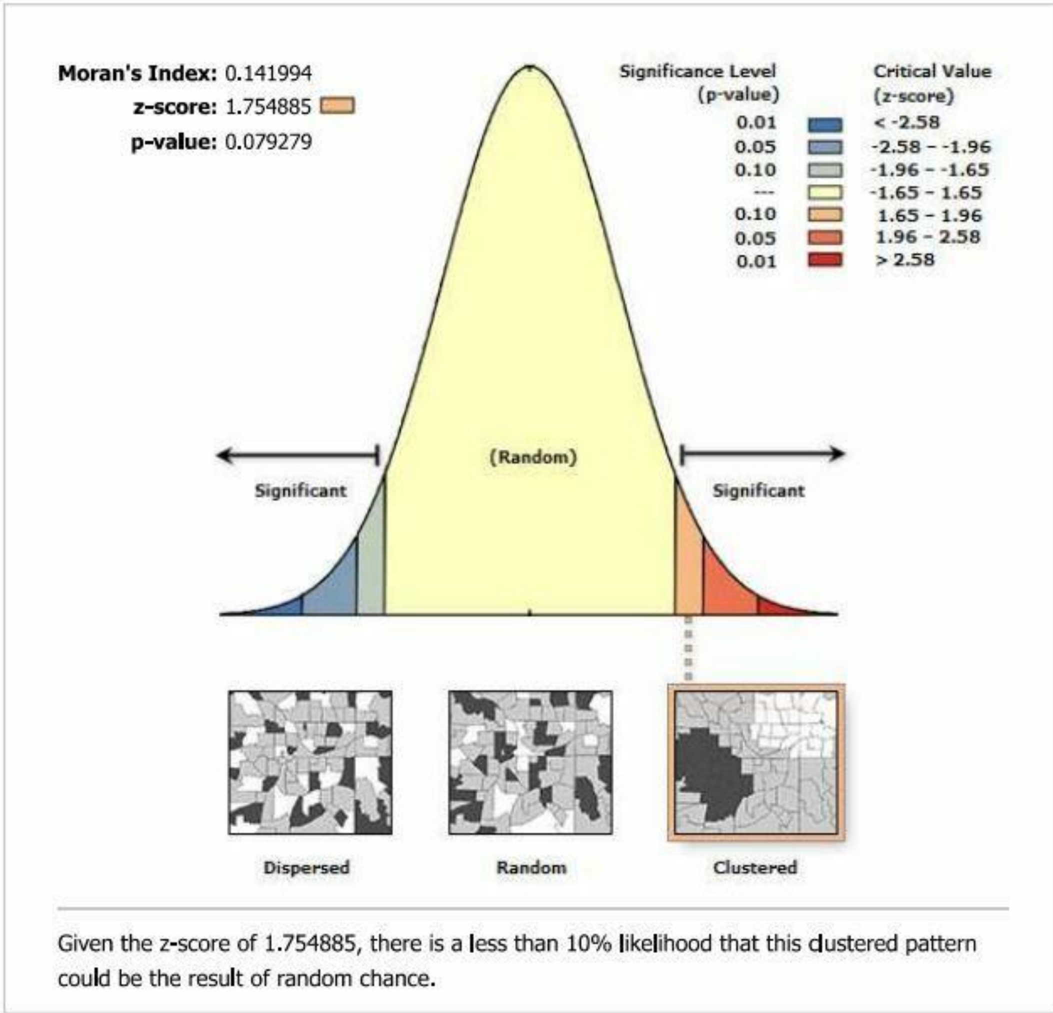

Given the z-score of 0.462672, the pattern does not appear to be significantly different than random.

### Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | -0.002224 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.007951 |
| **z-score:** | 0.462672 |
| **p-value:** | 0.643599 |

**Moran’s I analysis for 2019 Collisions**

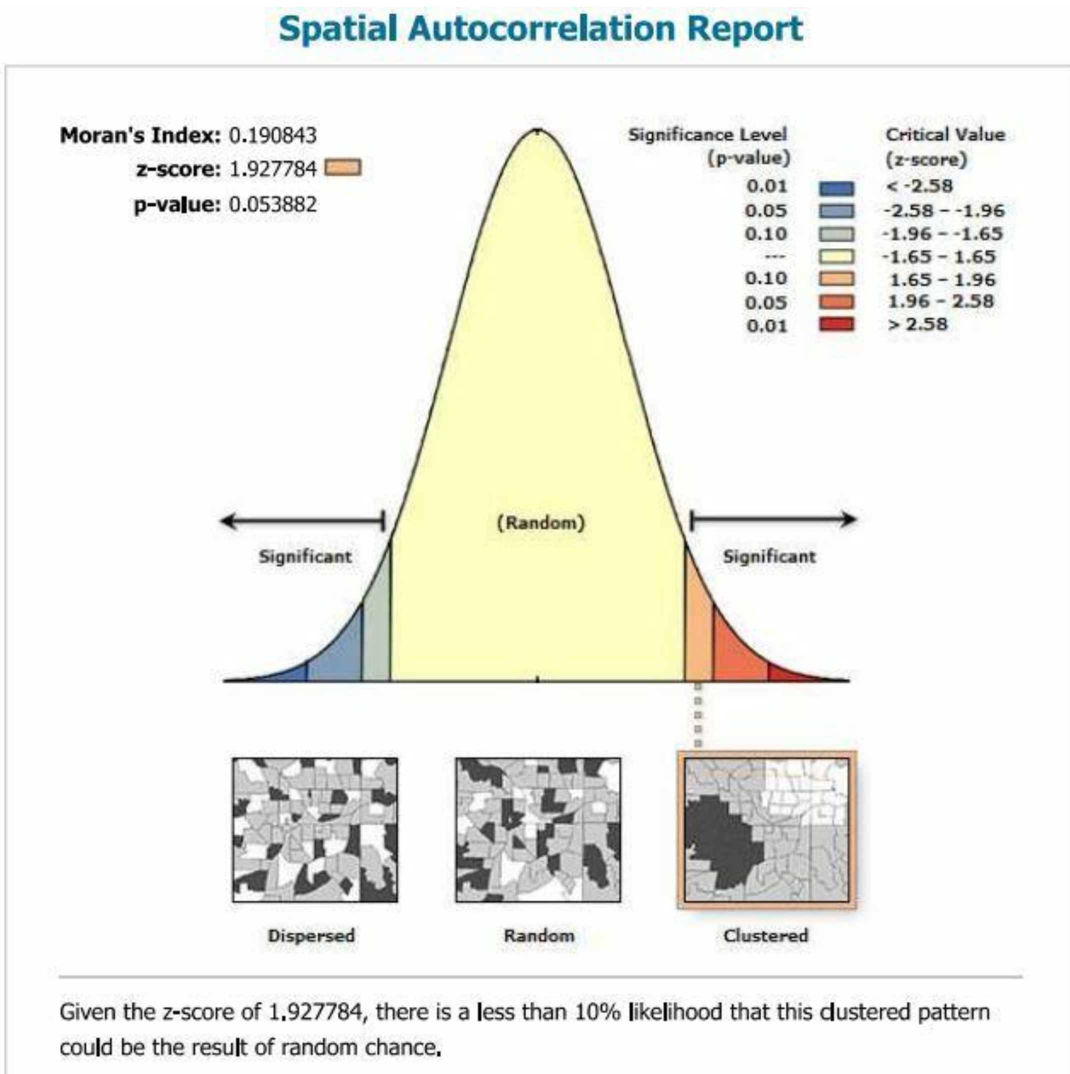
## Spatial Autocorrelation Report




## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.141994 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.011170 |
| **z-score:** | 1.754885 |
| **p-value:** | 0.079279 |

**Moran's I analysis for 2020 Collisions**

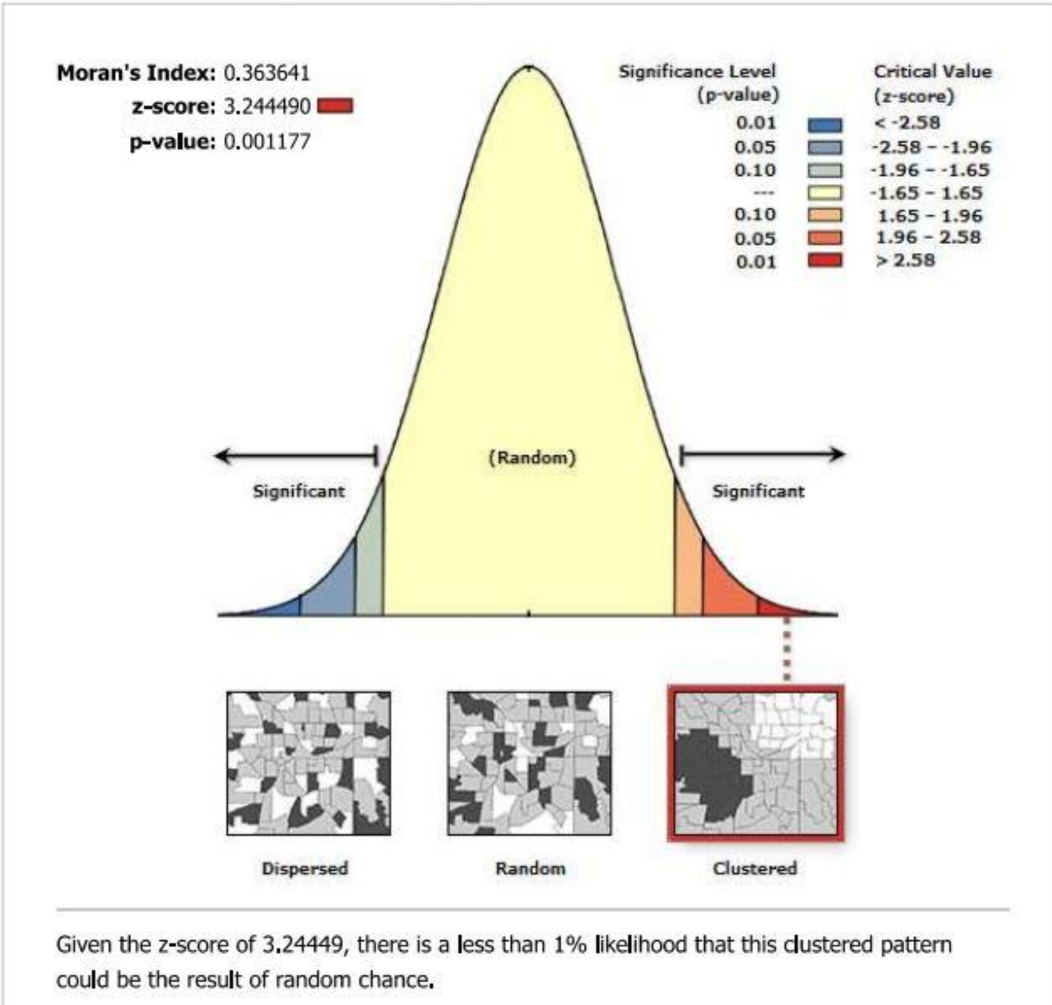



## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.190843 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.014774 |
| **z-score:** | 1.927784 |
| **p-value:** | 0.053882 |

**Moran's I analysis for 2019 TTI**

## Spatial Autocorrelation Report

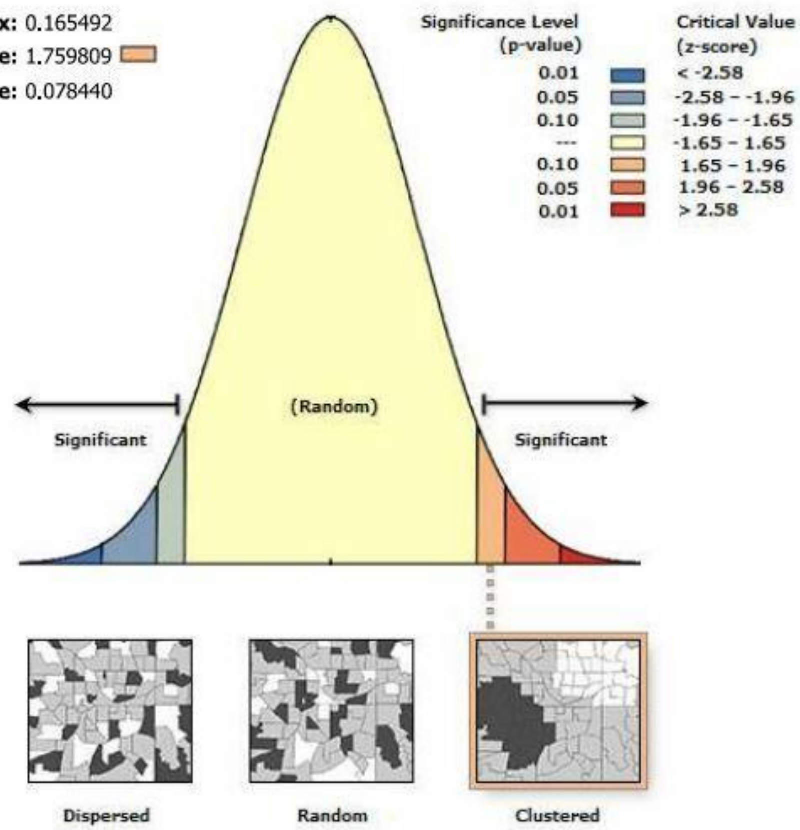



## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.363641 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.015745 |
| **z-score:** | 3.244490 |
| **p-value:** | 0.001177 |

**Moran's I analysis for 2019 PTI**

## Spatial Autocorrelation Report



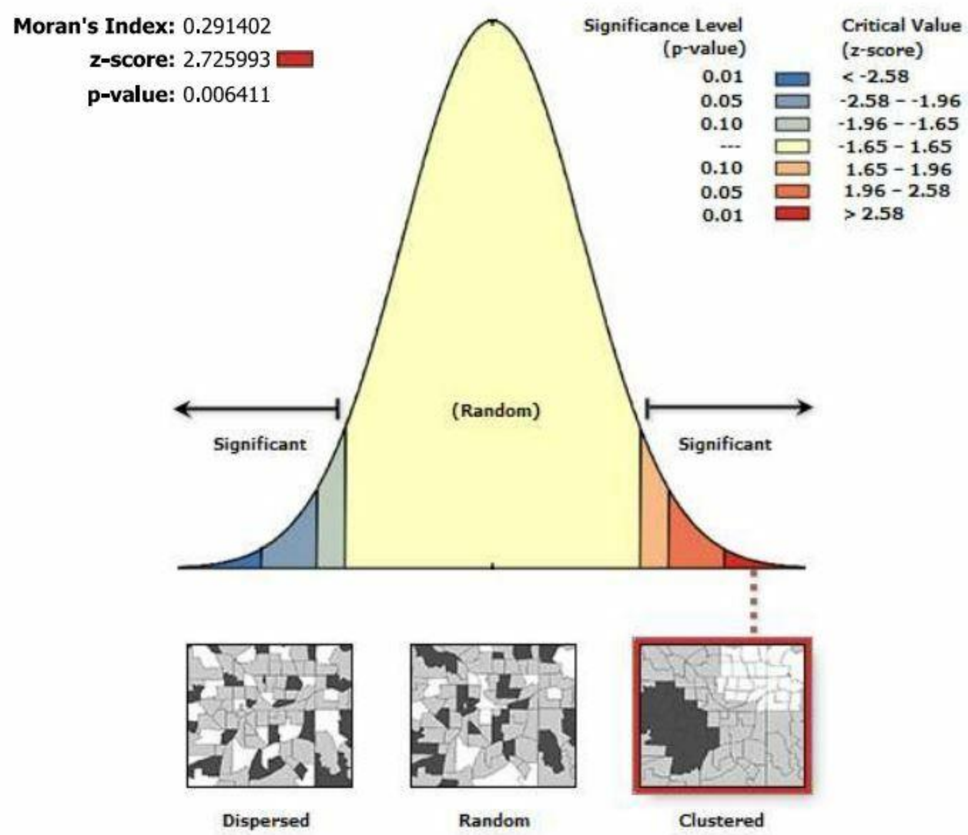

Given the z-score of 1.759809, there is a less than 10% likelihood that this clustered pattern could be the result of random chance.

## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.165492 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.014101 |
| **z-score:** | 1.759809 |
| **p-value:** | 0.078440 |

**Moran's I analysis for 2020 PTI**

## Spatial Autocorrelation Report



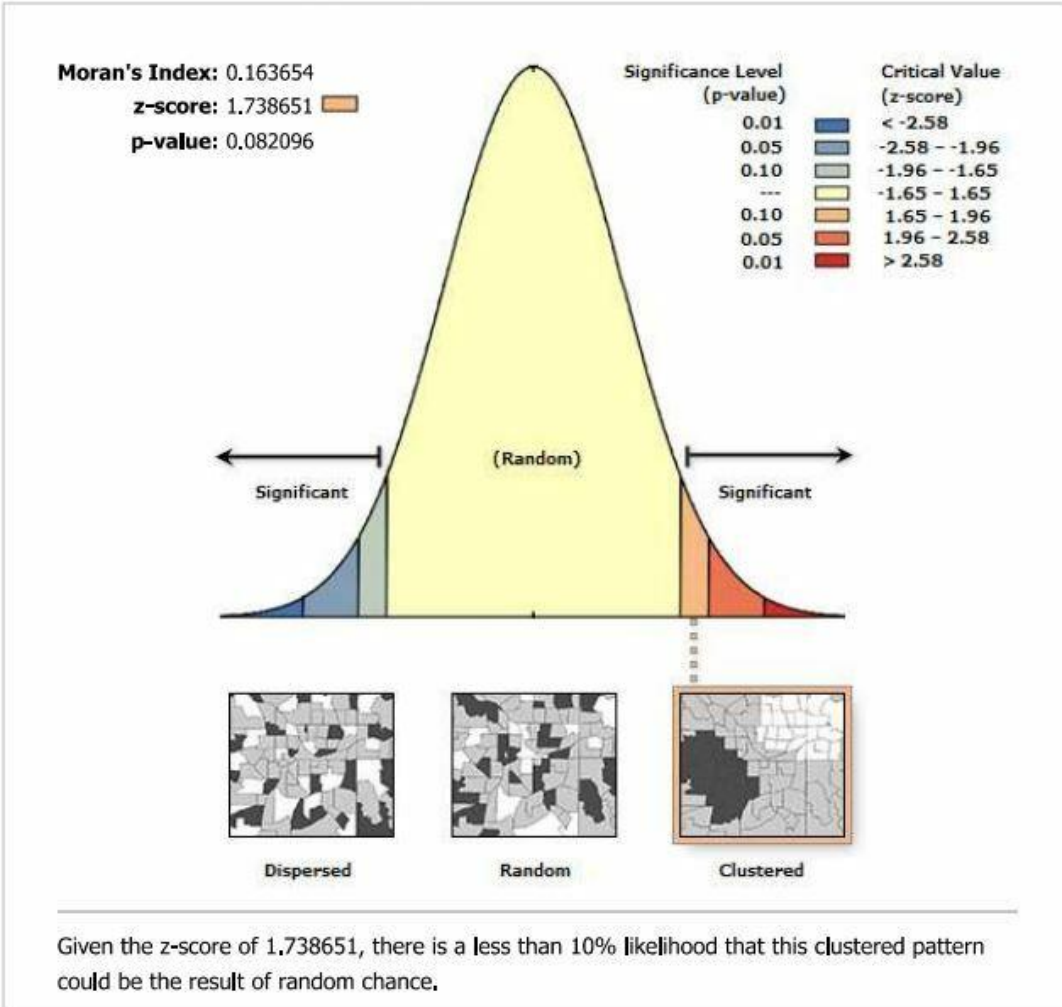

Given the z-score of 2.725993, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

## Global Moran's I Summary

| | |
|---:|---|
| **Moran's Index:** | 0.291402 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.015091 |
| **z-score:** | 2.725993 |
| **p-value:** | 0.006411 |

**Moran's I analysis for 2019 BI**

## Spatial Autocorrelation Report




## Global Moran's I Summary

| | |
|---|---|
| **Moran's Index:** | 0.163654 |
| **Expected Index:** | -0.043478 |
| **Variance:** | 0.014193 |
| **z-score:** | 1.738651 |
| **p-value:** | 0.082096 |

**Moran's I analysis for 2020 BI**