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Motor Vehicle Collisions in London, Ontario: Estimating the influence of the built environment and children's potential exposure

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Title

Motor Vehicle Collisions in London, Ontario: Estimating the influence of the built environment and children's potential exposure

Abstract

Motor vehicle collisions are the leading cause of death for children and youth worldwide. To effectively target interventions to improve child safety, it is necessary to identify where motor vehicle collisions occur most often and what factors make these areas more hazardous. Study #1 maps collisions in London, Ontario (2010-2019) and identifies hotspots using a network kernel density estimation method within a GIS. Logistic regression analysis revealed that bike lanes were negatively associated with hotspots, while sidewalks were positively associated. Study #2 estimated children's risk of being exposed to a motor vehicle collision while commuting to and from school, by combining collision risk data from study #1 with modelled student pedestrian volumes. Results suggest current crossing guard locations in London are not optimally deployed and should be relocated to the riskiest areas for student pedestrians. The findings of this thesis suggest that certain built environment characteristics have a significant influence on collision hotspots and should be considered in future road safety policy.

Keywords

Motor vehicle collisions; Geographic information systems; Built environment; Kernel density estimation; Hotspots; Child pedestrians

Summary for Lay Audience

Motor vehicle collisions are the leading cause of death for young people worldwide. To address this issue, we need to understand the factors causing severe motor vehicle collisions. We also need to identify the environments where young people face the greatest risk. First, motor vehicle collisions that occurred in London, Ontario were mapped. The concentration of these collisions were calculated to locate the areas with the most motor vehicle collision occurrence. When looking at areas around these high risk locations, we identified several factors that could be influencing the motor vehicle collisions. In particular, we found that bike lanes can lower collision occurrence and that sidewalks have increase motor vehicle collisions. Second, we estimated which roads and intersections children in London used to walk to school using home and school locations. The high risk locations that we identified previously were compared to areas with many students walking to school. We found that there were several areas that had many motor vehicle collisions and a higher number of students. Additionally, a majority of these areas were unsupervised. The current safety measures in London may need to be changed to ensure roads are safe for everyone. We have identified factors that may be causing and reducing motor vehicle collisions in London. The areas where children face the greatest collision risk were also identified. These findings provide a better understanding of motor vehicle collisions in London and should inform future methods to make roads safer.

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Chapter 1

1 Introduction

Globally, motor vehicle collisions (MVCs) have been a major cause of serious injury and death, totaling almost 1.35 million fatalities and around 50 million injuries in 2016 (World Health Organization, 2018). They are now the leading cause of death for children and young adults (5-29 years) worldwide (World Health Organization, 2018). The vehicle-centric culture in the North American context suggests that mobility and individual convenience is valued over the health and safety of the population. Cities have been designed for the automobile which presents accessibility and safety problems for all other road users. Public transit networks are difficult to implement due to demand and coverage issues while active transport users are tasked with the challenge of navigating a road network not designed for them. With increasing populations and subsequent increases in traffic volumes, there is a growing need to address issues surrounding road safety. While the advocacy for safe streets for the most vulnerable road users has been increasing in recent years, significant change to policy and road design is yet to be seen.

1.1 Background

1.1.1 Traffic Speed and Volume

The most significant predictors of MVCs are vehicle speed and traffic volume (Wang et al., 2013). There is a consensus in MVC literature that increased vehicle speed is not only associated with higher crash severity, but also with higher MVC occurrence (Dumbaugh & King, 2018; Wang et al., 2013, Aarts & van Schagen, 2006). This is due to higher impact velocities, shorter time to react and larger stopping distance requirements resulting in smaller margins for driver error. However, there are many other contributing factors to MVCs like road and traffic characteristics that make determining the exact relationship between speed and MVC occurrence difficult (Aarts & van Schagen, 2006). Traffic volume is another key predictor for MVC incidence. Overall, roads with higher traffic volumes tend to have higher occurrences of MVCs due to more vehicles and more opportunities for conflict between road users (Wang et al., 2013; Ewing & Dumbaugh, 2009). These results can be mixed as periods of extremely high traffic volume (congestion) decrease the vehicle speeds along a road and can have a reductive effect on MVC occurrence, particularly more severe collisions (Wang et al., 2013). Similarly, low traffic volumes may encourage increased vehicle speeds and may lead to higher incidences of severe MVCs. Existing studies typically use annual average daily traffic (AADT) for traffic volume data; however, it does not consider the temporal aspect of traffic volume. Traffic volume can vary from season to season as well as fluctuate throughout the day. As it becomes easier to collect and store massive amounts of data, it will be possible to study the patterns of traffic volume at a more granular level.

1.1.2 Demographic Characteristics

The populations most vulnerable to MVCs are children and elderly people, both when in vehicles and as pedestrians or cyclists. Elderly drivers have been shown to have a higher risk of MVC due to their slower reaction times and difficulty in perceiving other road users and hazards (Kim, 2019). Children are at higher risk for serious injury or fatality resulting from an MVC as occupants of a vehicle due to their smaller statures (Brolin et al., 2015). As pedestrians or cyclists, both children and elderly people are also more vulnerable to serious injury or fatality due to their weaker physical builds that are susceptible to severe impacts (Kim, 2019; Cloutier et al., 2021; Schwebel et al., 2012). Additionally, their typically slower walking speeds and unreliable perceptions of distance and vehicle speeds can lead to a propensity for poorer decisions and an inability to avoid traffic (Kim, 2019; Connelly et al., 1998). Children may be at even greater risk due to the promotion of active travel for school commutes, thereby exposing greater volumes of student pedestrians and cyclists to vehicular traffic (Cloutier et al., 2021).

1.1.3 Human Behavior

Much of the existing MVC literature focuses on three aspects of road safety: human behavior, vehicle design and built environment characteristics (Wang et al., 2013). Distracted driving behavior like cell phone usage and other secondary actions like eating or passenger conversation can avert eyes from the road and has been shown to increase the risk of MVC occurrence (Klauer et al., 2014), while impaired driving due to alcohol or drug use has also been shown extensively to increase MVC risk (Lefio et al., 2018; Morrison et al., 2003). Cell phone usage overall has risen in recent years, this extends to usage within vehicles by drivers which has led to an increase in MVC occurrence due to distracted driving (Wilson & Stimpson, 2010). The policy interventions implemented to address these undesirable behaviors, such as graduated driver licensing, law enforcement programs and road safety education programs have had varied and mixed results (Lefio et al., 2018; Dumbaugh et al., 2020, International Transport Forum, 2016; Morrison et al., 2003). Recent literature has suggested that current road design and practice affords drivers too much room for error, thereby promoting lackadaisical and careless driving behavior (Dumbaugh & King, 2018). Interventions regarding human behavior, educational programs in particular, typically target pedestrian and cyclist behavior rather than driver behavior. Policies and road design should be implemented in a way that places the responsibility for road safety on all road users and encourage drivers to be more attentive and exercise more caution. The vulnerability of children to MVCs is partially attributed to their relative lack of experience in navigating roadways, which is usually addressed through educational programming. However, this perpetuates a victim-blaming narrative, drivers should also be cognizant of the vulnerability of other road users and act accordingly.

1.1.4 Vehicle Design

Vehicle design is also a major part of safety research in the overall MVC literature, particularly among engineers. Longstanding practice in vehicle safety focuses on the crashworthiness or the level of occupant protection of a vehicle (International Transport Forum, 2016). However, this has not reduced the incidence of MVCs and has only reduced the risk of injury for the occupants of a vehicle, disregarding other road users. A shift in road safety responsibility to encompass automobile manufacturers has led to research in vehicle safety that emphasizes the need to reduce vehicle speeds and enhance the attentiveness and awareness of drivers (International Transport Forum, 2016; Cloutier et al., 2021; Dumbaugh & King, 2018). This has led to developments in crash avoidance technology like autonomous emergency braking and intelligent speed assistance technologies (International Transport Forum, 2016). However, these technologies are not yet widely implemented and so their impact on MVCs is yet to be seen. In recent years, touch screens are being implemented in vehicles for navigational and entertainment purposes, in addition to existing radio equipment. However, this has been shown to have a potentially adverse effect on road safety as it may present a distraction for drivers and avert eyes from the road (Perez, 2012).

1.1.5 Environmental Conditions

MVC literature surrounding environmental characteristics analyze how changes in season, weather and time of day influence MVCs. The impact of winter and winter precipitation on MVC incidence is well documented, showing increases in MVCs during winter storms (Mills et al., 2019). However, the impact on crash severity is mixed. At the most extreme winter conditions, the risk of injury from an MVC decreases compared to more moderate winter conditions (Mills et al., 2019). Although more research needs to be done to determine the reasons behind the decrease in crash severity, it is theorized that it is a combination of more cautious driving, the broadcasting of weather warnings and the commencement of road maintenance (Mills et al., 2019). During summer months, it is more likely that severe MVCs occur at higher rates because higher pedestrian volumes create more opportunity for conflict between vulnerable road users (Sebert Kuhlmann et al., 2009; Cloutier et al., 2021). Additionally, MVC occurrence and severity has been seen to increase during periods of heavy precipitation, a result of slippery road surfaces and reduced visibility (Eisenberg, 2004; Andrey et al., 2003). The increase in traffic volume during rush hours typically lead to an increase in MVC incidence due to more opportunities for conflict between vehicles (Martin, 2002). After sunlight hours, the lack of light and less traffic on roads lead to greater MVC severity due to a lack of visibility and greater vehicle speeds (Martin, 2002).

1.1.6 Built Environment

The built environment has been touted to have the greatest potential impact on road safety due to its direct and constant influence on road users. Traditionally, much of the literature regarding built environment influences on MVCs has been written by engineers (Dumbaugh & King, 2018). However, planners are increasingly being involved in contemporary road design, shifting the focus from vehicle-centric considerations to encompassing all road users (Dumbaugh & King, 2018). Existing literature focuses on reducing vehicle speed, reducing conflict points between road users and increasing visibility.

1.1.6.1 Traffic Calming Features

Attempts to reduce vehicle speed typically come in the form of various traffic calming features. Several studies have found that wider road widths have negative effects on road safety (Ewing & Dumbaugh, 2009; Stoker et al., 2015; Retting et al., 2003). Although this may increase traffic congestion in certain areas, narrower streets and lanes may influence drivers to drive slower, more passively and with more care (Ewing & Dumbaugh, 2009). Street side elements like street trees, planters, benches and bike lanes also have a narrowing effect on the street, reducing the perception of free and open road that drivers might otherwise have (Dumbaugh & King, 2018). Features on the road itself like traffic islands and medians also create a narrowing effect in addition to physically separating traffic (Dumbaugh & King, 2018). More active traffic calming measures like speed humps and roundabouts have also been shown to be effective in reducing vehicle speed and MVC incidence (Ewing & Dumbaugh, 2009; Retting et al., 2003; Stoker et al., 2015; Rothman et al., 2015; International Transport Forum, 2016). These may be more cost-effective approaches than road/lane narrowing, but also only have a calming effect at targeted areas.

1.1.6.2 Exposure Reduction

The risk of MVC occurrence often increases in areas where high volumes of pedestrians or cyclists are exposed to high volumes of vehicles (Retting et al., 2003; Stoker et al., 2015). The reduction of conflict points and exposure between road users where possible typically falls within the domain of the built environment. Four-way intersections are typically more hazardous than three-way intersections due to more conflict points between vehicles and with other road users (Dumbaugh & Li, 2010; Miranda-Moreno et al., 2011). Traffic signals at intersections, however, are an example of a temporal separation between pedestrians and vehicles. Vehicle-centric intersections that prioritize vehicle movement mean pedestrians often have little time to cross wide roads and have to navigate turning vehicles (Dumbaugh & King, 2018). While signalized intersections are effective in controlling vehicular traffic, they affect traffic flows and are not realistic to be implemented city-wide. Intersections that implement pedestrian exclusive phases (split-phasing), which stop all vehicular traffic to allow pedestrians to cross, or leading pedestrian intervals have been shown to be effective in reducing MVCs (Dumbaugh & King, 2018; Retting et al., 2003). Built environment measures that eliminate pedestrian-vehicle exposure at intersections entirely, like overpasses and underpasses are highly effective but are resource intensive and can be aesthetically intrusive (Retting et al., 2003; Stoker et al., 2015). Medians in the middle of roads act as exposure reduction between vehicles while traffic islands provide refuge spaces for crossing pedestrians which have also been shown to reduce pedestrian-vehicle exposure (Ewing & Dumbaugh, 2009; Retting et al., 2003; Stoker et al., 2015; Dumbaugh & King, 2018; International Transport Forum, 2016). Modern roundabouts and traffic circles are able to reduce conflict points between vehicles when entering an intersection and allow for efficient vehicle movement (Ewing & Dumbaugh, 2009; Retting et al., 2003). Single-lane roundabouts in particular have been shown to have lower pedestrian MVC incidence than comparable intersections with traffic signals (Ewing & Dumbaugh, 2009; Retting et al., 2003). While larger multi-lane roundabouts are effective in reducing MVC rates between vehicles, they may present accessibility issues for elderly and disabled pedestrians and force pedestrians to cross multiple lanes of traffic without signal. (Ewing & Dumbaugh, 2009; Retting et al., 2003). Street side elements that separate vehicles from pedestrians like street trees and planters on sidewalks act as barriers between vehicles and pedestrians, reducing the exposure of pedestrians to vehicles (Ewing & Dumbaugh, 2009; Dumbaugh & King, 2018; Naderi, 2003). However, this does not affect fixed-object collisions, when vehicles collide with a roadside object like a street tree, telephone pole or parked car (Ewing & Dumbaugh, 2009; Dumbaugh & King, 2018). Bike lanes are not only effective in separating cyclists from vehicular traffic, but also act as a buffer for pedestrians, reducing exposure and potential conflict points (Reynolds et al., 2009).

1.1.6.3 Improving Visibility

Literature on visibility has mainly focused on improving street lighting, but sightlines are an important element to consider as well. A few studies considered on-street parking as a feature that could potentially block the sightlines of drivers, rendering them slow to react if a pedestrian steps out quickly into traffic (Ewing & Dumbaugh, 2009; Retting et al., 2003). Retting et al. suggest the implementation of diagonal on-street parking, this could help improve pedestrian visibility and reduce car door-bicycle collisions (2003). Conventional practice recommends that drivers have an unobstructed view of the entire intersection, resulting in the removal of street side elements like traffic control cabinets, hedges or on-street parking around an intersection (Dumbaugh & King, 2018). However, more recent recommendations suggest that narrower roads and more compact intersections, instead of street side element removal, can increase visibility for drivers as well as their awareness and attentiveness (Dumbaugh & King, 2018). This is because slower vehicle speeds reduce the recommended sightline distance that drivers need to make a safe and informed decision (Transport Association of Canada, 2011). Driveways can also be quite hazardous areas as there is often a lack of visibility in these areas due to hedges and other similar street side elements (Dumbaugh & King, 2018). Several studies have shown the effectiveness of street lighting on increasing visibility and reducing MVCs, but there is a lack of research regarding driver sightlines (Retting et al., 2003; Stoker et al., 2015).

1.1.7 Vision Zero

The recent epidemic of MVCs has led to the adoption of Vision Zero, a road safety policy originating from Sweden, by many governments around the world (Kim et al., 2017). Vision Zero is a policy that reframes MVCs as a public health problem, suggesting that MVCs are a preventable health hazard rather than a random unpreventable occurrence (Kim et al., 2017). Vision Zero also postulates that road users (drivers, pedestrians, cyclists) are not the only ones to be held accountable for a MVC but that automobile manufacturers, transport engineers, planners and many more actors should also be held responsible for road safety (Kim et al., 2017). The core tenet of the policy is that no deaths or serious injuries should result from MVCs, challenging the notion that convenience and mobility are worth the health and safety risks (Kim et al., 2017). The City of London is one of a few cities in Ontario which have adopted Vision Zero in their road safety strategy, presenting an opportunity to examine the impact of the policy framework on road safety in London since its adoption in 2017 (City of London, 2018). A Complete Streets Design Manual for the City of London has been created with the Vision Zero framework as a policy priority, solidifying the City's intent to address road safety (City of London, 2018). A Vision Zero approach would mean a shift from educational programs and law enforcement policies to the implementation of built environment interventions, vehicle technology advancements and a prioritization of vulnerable road users.

1.1.8 Active Transportation to School

MVCs are the leading cause of death for school-age children worldwide, which is indicative of the burden of this acute public health issue (World Health Organization, 2018). Studies have found that children are at more risk of pedestrian MVCs, due to their physical vulnerabilities (Stevenson et al., 2015) and limited experience in navigating roadways (Schwebel et al. 2012). The lack of visibility of children due to their small stature has been an issue for drivers and increases the risk of MVC occurrence (Barton & Schwebel, 2007; Stoker et al., 2015). Existing literature has found that most child pedestrian MVCs occur in areas near their home (Stevenson et al., 1996; Braddock et al., 1994; Rothman et al., 2014) and near their school (Warsh et al., 2009; LaScala et al., 2004). While there has been recent promotion of active travel to school as a method to increase the physical activity and overall health of children (Sallis et al., 2006; Faulkner et al., 2009; Larsen et al., 2009; Buttazzoni et al., 2019), more child pedestrians walking to school may increase the risk of MVC occurrence (Stoker et al., 2015; Clark et al., 2016; Larsen et al., 2012). The safety and walkability of the pedestrian environment is not only important for child safety, but also influences the rates of active travel to school due to parental and student perceptions (Timperio et al., 2006). Active school travel programs like Active & Safe Routes to School (http://www.activesaferoutes.ca/) have been shown to have positive effects on active travel to school and in reducing children's and parents' perceived barriers to active travel (Buttazzoni et al., 2019).

1.2 Research Objectives and Questions

The prevalence and burden of MVCs has been shown to be a significant danger to today's populations, particularly to younger populations that will take over from the current generations. This highlights the need to further improve knowledge of road safety and inform decisions that can ensure the health of future populations. This thesis seeks to understand MVCs and road safety issues within London, Ontario. The first objective of this work is to use recent MVC data to map and study the prevalence of MVCs across London, Ontario and over time. The second objective of this thesis is then to assess how the spatial distribution of riskier areas within the street network, relate to potential active travel by students pedestrians on route to school. To address these research objectives this thesis seeks to answer the following Research Questions.

RQ1. Where are MVC hotspots located within London, Ontario and what are their trends over time?

RQ2. How do the built environment characteristics of London's street network relate to MVC hotspots?

RQ3. Where are school-age children walking to school in London exposed to high MVC risk?

RQ4. How well do crossing guards align with the location of high-risk areas for student pedestrians on route to school?

The findings of this study should further inform local research on the characteristics and factors influencing MVC hotspots. The findings of this thesis should also promote the future analysis of the temporality of MVC hotspots and the understanding of how and why hotspots are changing. Importantly, the findings of this study should inform the policy and road design decisions in London in order to ensure the safety of all road users in accordance with Vision Zero principles, specifically associated with active transportation to school by student pedestrians.

1.3 Study Area

This study was conducted in the city of London, located in the southwestern part of Ontario (Figure 1-2). As of 2021, the city had a population of 422,324, a 10% growth since the 2016 census (383,822) which was a 4.8% growth from the 2011 census (366,151) (Statistics Canada, 2011; Statistics Canada, 2016; Statistics Canada 2021). The long-standing auto-centric culture and the recent adoption of Vision Zero, a road safety policy framework, in 2017 presents an opportunity to assess the MVC issues in the context of London, Ontario.

London has around 1,900 km of road, generally arranged in a grid pattern in areas around the city center (Figure 1-1a) and in a block grid with loops and cul-de-sacs pattern in the more suburban neighborhoods (Figure 1-1b). London has 5,301 intersections, around 7.78 % of which being signalized. For the period January 2010 to December 2019 inclusive, the City of London had an average of 7,728 motor vehicle collisions (MVCs) per year.

Figure 1-1: a) Grid street network pattern in downtown London and b) block-grid with loop and cul-de-sac street network pattern in suburban northwest London.

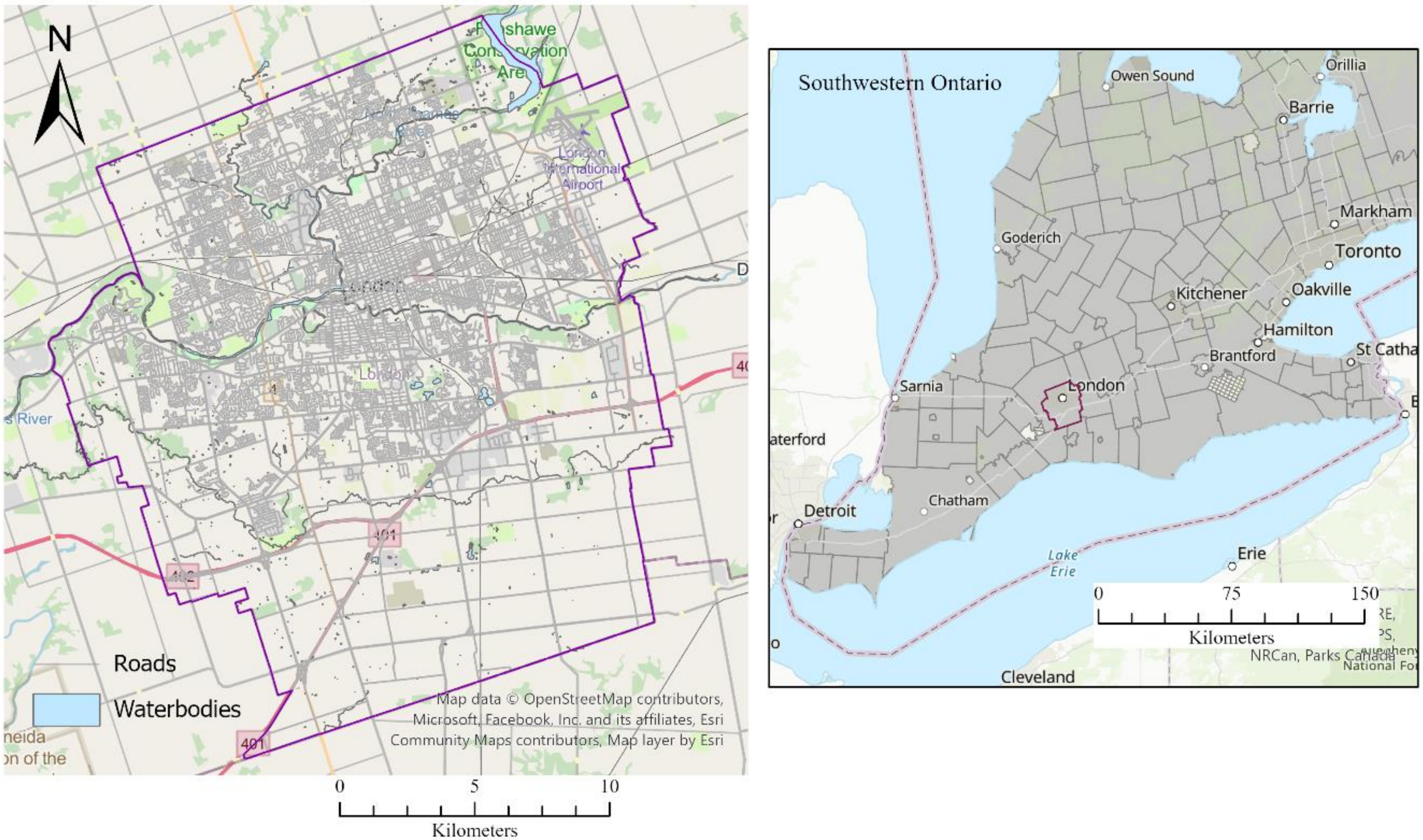

Figure 1-2: Study area map showing London, Ontario within southwestern Ontario, Canada. The grey polygons in the inset map are lower and single-tier municipalities in Ontario, while the study area is shown as a purple outline.

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Chapter 2

2 Assessing the Influence of the Built Environment on Spatio-temporal Motor Vehicle Collision Hotspots in London, Ontario

2.1 Introduction

The identification of motor vehicle collision (MVC) hotspots has played a crucial role in the efficient distribution and implementation of road safety measures. Various methods have been employed in MVC hotspot identification. Planar kernel density estimation (KDE) (Anderson, 2009) and more recently network-based KDE (Xie & Yan, 2008) have been popular methods in the literature. KDE was deemed advantageous for MVC hotspot analysis because it can determine the spread of risk around a cluster of MVCs, identifying dangerous areas rather than points. This is useful in MVC analysis as the areas surrounding the location of an MVC are typically just as hazardous as the point of incidence. Further, network-based KDE is agreed to be more appropriate for network-constrained phenomena like MVCs than conventional KDE; rather than the MVC risk being spread across a circular area, the risk is spread along the road network (Xie & Yan, 2008).

Conventional KDE also has a tendency to overestimate hotspots on network-constrained phenomena due to its inherent assumption of Euclidean distance (Yamada & Thill, 2007). Multiple studies have attempted to address this issue by modifying conventional KDE into tools like KDE+ (Bil et al., 2016), which applies a KDE method with cluster ranking to a line network, or extending K-function methods to a network using Spatial Analysis on a NETwork (SANET) (Okabe et al., 2005). Xie and Yan have developed a network-based KDE (2008) for MVC analysis which was implemented in R by Branion-Calles (2020) and was utilized in this study. The KDE+ tool is promising, but is unable to analyze smaller road segments, aggregating MVCs onto longer road segments which may dilute local hotspot patterns. In terms of hotspot definition and categorization, there is no consensus, particularly in MVC literature (Anderson, 2009; Bil et al., 2019; Thakali et al., 2015). ESRI's Emerging Hotspot Analysis tool has been widely used across many fields, including road safety, to assess temporal trends and categorize hotspots (Cheng et al., 2019; Betty et al., 2020; Harris et al., 2017). However, ESRI's utilization of a space-time cube means it is difficult to apply to point events constrained to a network, like MVCs.

Previous studies in MVC literature have assessed the built environment's influence on MVCs (Ewing & Dumbaugh, 2009; Dumbaugh & King, 2018) and identified demographic and crash-related risk factors affecting MVC severity (Al-Ghamdi, 2002; Chen et al., 2012). In order to identify MVC hotspots and determine the spread of MVC risk, a variety of methods have been developed (Bil et al., 2016; Xie & Yan, 2008; Anderson, 2009). Several studies have assessed MVC hotspot trends using ESRI's Emerging Hotspot Analysis tool but lack road network level analysis (Cheng et al., 2019), while a study has developed a novel method of assessing temporal hotspot trends using moving time windows (Bil et al., 2019). However, few studies have identified how MVC hotspots are changing over time and assessed how built environment characteristics influence those MVC hotspots.

2.1.1 Research Objective

To understand how MVCs in London, Ontario are changing over time, MVC hotspots will be identified for every year in the study period (2010-2019) using the network-based KDE analysis developed by Xie and Yan (2008). The temporal trend of these hotspots will be assessed and used as the typology on which to analyze built environment influence. By examining how built environment characteristics influence these MVC hotspots, this analysis will lead to a better understanding of what may be associated with MVCs and how they can be addressed. It is expected that considerations to road safety policy and road design can be made through the interpretation of this study's results.

2.2 Methods

2.2.1 Data

2.2.1.1 Motor Vehicle Collision Data

MVC data from January 2010 to February 2020 was obtained from the City of London, Ontario, Canada. The data include the time and date of each MVC, collision type (automobile vs automobile, automobile vs cyclist, automobile vs pedestrian), severity of collision (property damage only, injury, fatality), demographic information of the participants involved (age, sex), participant condition (normal, impaired, etc.), participant action (proper action, erratic/incorrect action), vehicle condition (normal, in need of repair), environmental characteristics (lighting condition, weather) and reason(s) for collision. Any missing coordinates were manually inputted using the street names provided in the data. MVC data that did not have coordinates or street names and thus were unable to be identified were excluded (< 0.5% of the data were excluded this way). We selected MVC data from January 2010 to December 2019, inclusive. We chose to exclude data from 2020, as trends in MVCs were likely to be significantly impacted by COVID-19 and stay at home policies (Rapoport et al., 2021; Stiles et al., 2021).

The MVC data were further cleaned, removing a small number of records where the data were missing or erroneous. In some cases, vehicle information was missing, coordinates were missing or were outside of the city of London. This study focused on MVCs classified as an injury or fatality, therefore the 65,486 of 78,276 (84.12%) MVCs classified as property damage only (PDO) were excluded from the analysis. This is in-line with Vision Zero's goal of no serious injuries and fatalities resulting from MVCs (Kim et al., 2017). This analysis, therefore, includes all collision types, automobile-automobile, automobile-cyclist and automobile-pedestrian that resulted in a serious injury or fatality (n = 12,283 MVCs) (Figure 2-1).

Figure 2-1: Motor vehicle collisions (n = 12,283) that resulted in injury or fatality during the years 2010-2019 in London, Ontario are shown in purple along with the road network in grey.

2.2.1.2 Road Network and Traffic Volume Data

The road network segments and intersections data, and traffic volume for most major arterials, collectors and roads were available through the City of London's Open Data site (https://opendata.london.ca/). However, the traffic volume of many of the smaller local roads and secondary collectors was not available. The missing traffic volumes were assigned to the roads according to their street classification to estimate traffic volume for all streets in the analysis (Table 2-1; Figure 2-2). In certain cases, the traffic volumes were estimated based on surrounding traffic volumes and manually inputted due to the unique characteristics of the roads in specific areas (i.e. Western University, Fanshawe College and Victoria Hospital). The traffic volume at intersections was calculated by summing the total traffic volume for all segments in the intersection and dividing that number by two. This is based on the rationale that when a vehicle enters and exits an intersection, it touches exactly two segments.

Table 2-1: Values used to estimate annual average daily traffic for street segments where no official data was recorded.

Street Classification	**Assigned Estimated Annual Average Daily Traffic (AADT)**
Local	250
Secondary Collector	1000
Primary Collector	5000
Arterial	10000
Freeway	15000
Ramp	2500

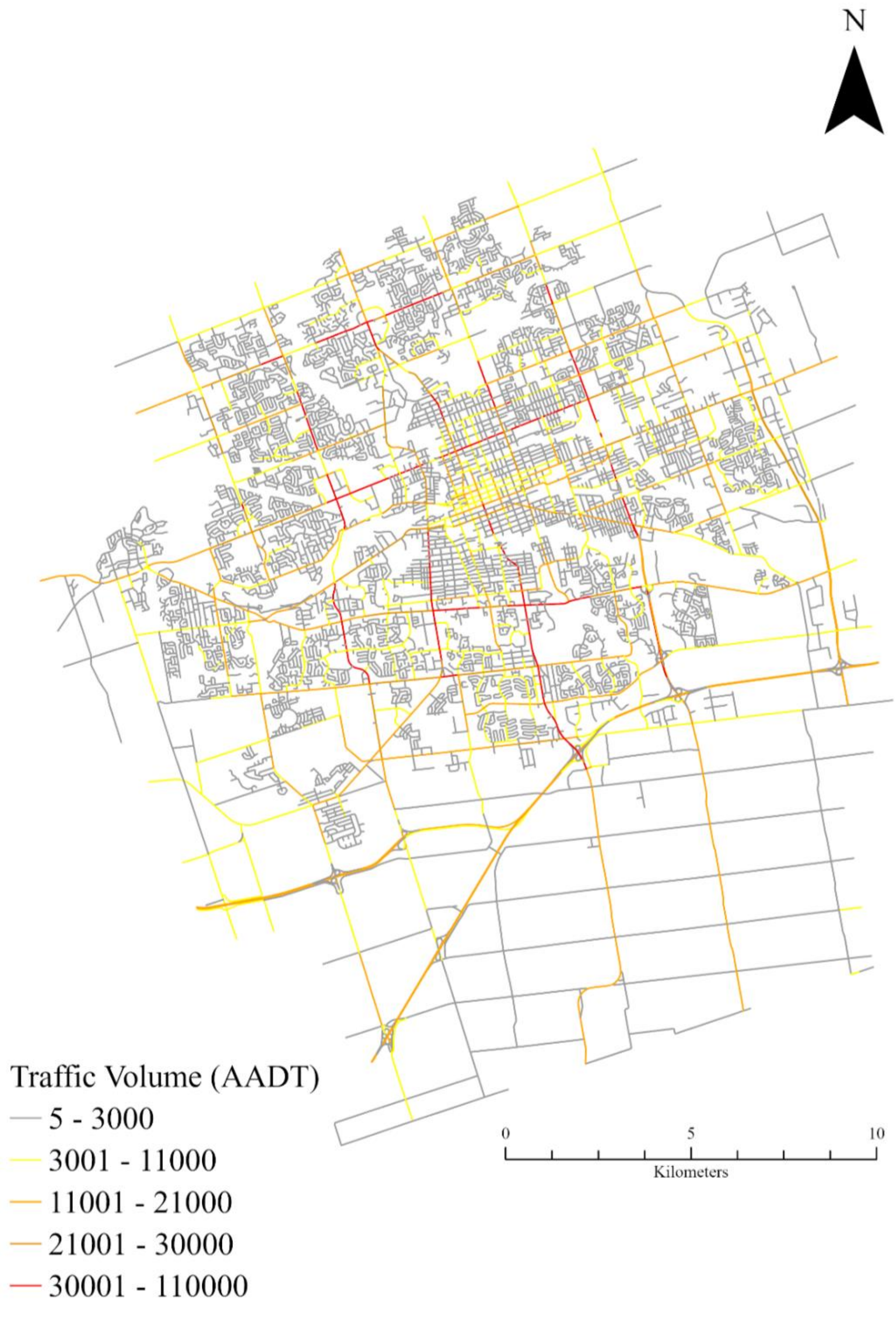

Figure 2-2: The traffic volume in London, Ontario shown in annual average daily traffic by road segment.

2.2.1.3 Separation of Intersections and Mid-Block Road Segments

This study will assess MVCs occurring at both intersections and mid-block road segments. It is important to differentiate the two types of locations of collisions as previous studies have shown the characteristics of MVCs occurring in these areas differ (Al-Ghamdi, 2003; Lightstone et al., 2001). Subsequent analyses were performed separately on the two sets (mid-block segments and intersections) of data.

2.2.1.4 Lixelization

This analysis framework uses *lixels*, a term coined by Xie and Yan (2008) which essentially is a linear pixel, as the unit of analysis for mid-block segments. For analysis along a linear network like a road network, this was deemed the most appropriate approach as it allows for a more straightforward method of creating units of similar size for network analysis (Xie & Yan, 2008). First, London's single line road network was split into segments bound by intersections or end points (dead ends), resulting in 9,546 road segments. Each segment was then divided into equal length lixels with a maximum length of 25m. For example, a road segment that was 247.5m in length would be split into ten lixels that are 24.75m in length (Figure 2-3). In total, 80,671 lixels were created from the road network with an average length of 23.6m overall. The maximum lixel length of 25m was determined as the most appropriate balance between detail in local variation in hotspot patterns and computational efficiency (Xie & Yan, 2008; Branion-Calles, 2020).

Figure 2-3: a) Example of a 247.5m segment (Farrah Road) highlighted in light blue and b) One of ten 24.75m lixels along a Farrah Road segment highlighted in light blue.

2.2.1.5 Built Environment Variables

The environmental variables chosen for the models have been established in MVC literature as factors that influence MVC incidence and/or severity (see Table 2-2). Street lights are important for the visibility of pedestrians in low light, having a reductive effect on night-time pedestrian MVCs (Retting et al., 2003; Stoker et al., 2015). Bike lanes have been shown to be effective in reducing vehicle exposure by separating traffic from cyclists and pedestrians (Reynolds et al., 2009). Hedges have the potential to block sightlines of drivers, which can create hazardous and risky situations (Dumbaugh & King, 2018). Driveways create conflict points similar to intersections, and can increase MVC incidence (Dumbaugh & King, 2018). Streets with sidewalks alongside them have been found to have less MVCs involving pedestrians than streets without sidewalks (Ewing & Dumbaugh, 2009). Street trees have been shown to have negative effects on MVCs, having a traffic calming effect and acting as a barrier between vehicles and the sidewalk (Dumbaugh & King, 2018). On-street parking is also thought to have a traffic calming effect, by temporarily narrowing the road, but also has been shown to decrease pedestrian visibility (Ewing & Dumbaugh, 2009; Retting et al., 2003). Road width has been discussed widely as a significant factor in influencing vehicle speeds, which in turn influences MVC severity (Ewing & Dumbaugh, 2009; Dumbaugh & King, 2018; Stoker et al., 2015; Retting et al., 2003). Traffic signals are effective in temporally separating road users, which reduces the opportunities for conflict (Dumbaugh & King, 2018). Simpler intersections, intersections that have fewer converging roads than a normal, four-way intersection, has less conflict points which should result in fewer MVCs (Dumbaugh & Li, 2010; Miranda-Moreno et al., 2011).

All environmental data was sourced from the City of London’s Open Data site. Road width categorizations were estimated based on a recommended lane width according to the Complete Streets Design Manual (City of London, 2018).

Table 2-2: Built environment variables and their corresponding code descriptions.

Variable	Code/Value	Model	Type
Hotspot*	1 = Hotspot 0 = Baseline (Not a Hotspot)	Both	Binary
Street Lights	1 = Street light presence 0 = No street light presence It is assumed that all street lights are functional as data on functionality was not available	Both	Binary
Bike Lanes	1 = Bike lane presence 0 = No bike lane presence	Both	Binary
Hedges	1 = Hedge presence 0 = No hedge presence	Both	Binary
Driveways	The number of driveways in the vicinity of a given lixel.	Mid-block	Continuous
Sidewalks	1 = Sidewalk presence 0 = No sidewalk presence	Both	Binary
Trees	The number of trees in the vicinity of a given lixel or intersection.	Both	Continuous
Parking	1 = On-street parking presence 0 = No on-street parking presence	Mid-block	Binary
Road Width	Narrow = <7m Medium = between 7m and 14m Wide = >14m	Mid-Block	Categorical
Average Road Width	Narrow = <7m Medium = between 7m and 14m Wide = >14m	Intersection	Categorical
Signalized Intersection	1 = Intersection is signalized 0 = Intersection is not signalized	Intersection	Binary
Converging Roads	Simple = <3 roads Medium = 4 roads Complex = >5 roads	Intersection	Categorical

The decision to use lixels as the unit on which to conduct analysis for mid-block segments meant that the road characteristic data was also attached to each lixel. To do this, GIS analysis was used to detect whether built environment variables were within a 23.5m buffer of a given lixel (Figure 2-4a). A buffer distance of 23.5m was established by sampling several main roads and determining the distance that most accurately covered the necessary environmental variables (Figure 2-4b). The road width for lixels were calculated by taking the distance of the centerline of a road to the road edge and multiplying it by two. Although this does not account for medians and traffic islands, the difference in road width these features make are minimal.

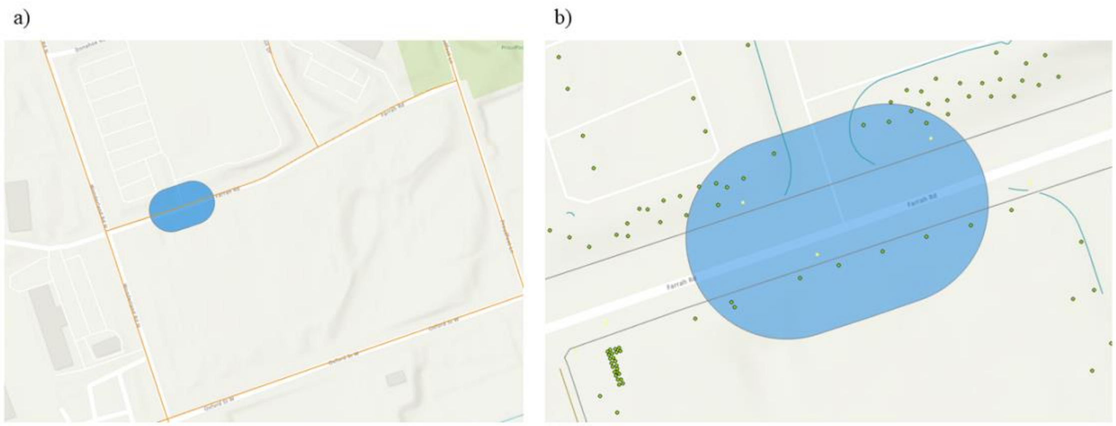

Figure 2-4: a) A lixel on Farrah Road with a 23.5m buffer then b) displayed with built environment variables. A buffered lixel on Farrah Road displayed with built environment variables. Street trees are in green, streetlights in yellow, sidewalks in grey and driveways in teal. This lixel would be attributed as having street light presence, sidewalk presence, driveway presence and as having 16 street trees.

Built environment variables were attributed to an intersection if they were within a 25m buffer distance (Figure 2-5). This distance was used to account for the lengths of the lixels converging at an intersection that were deemed as part of that intersection. The average road width of roads converging at an intersection was used as a proxy for intersection size. The variables were assumed to be functional and of consistent quality or size. For example, street lights were assumed to be working and hedges were assumed to be of the same size.

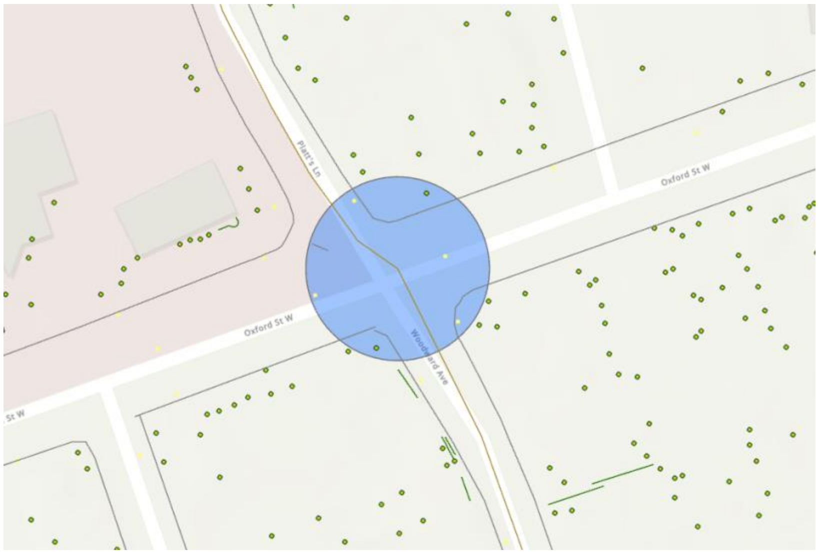

Figure 2-5: An intersection with a buffer of 25m shown with built environment variables. This intersection would be assigned as having streetlight presence, sidewalk presence, bike lane presence (brown line) and two street trees.

2.2.2 Data Analysis

2.2.2.1 Network Kernel Density Estimation

To identify MVC hotspots in London, Ontario, a network-based KDE method was used. Existing studies have used a planar-based KDE approach when identifying MVC densities and hotspots (Anderson, 2009; Erdogan et al., 2008). However, conventional planar-based KDE uses Euclidean space, which when used to analyze a phenomenon restricted to a network space, tends to overestimate and over identify clusters (Yamada & Thill, 2007; Xie & Yan, 2008). Network-based KDE was therefore chosen because network-based KDE considers that MVCs are constrained to the road network and thus is able to provide a more accurate identification of hotspots. This study uses the form proposed by Xie and Yan (2008) as the kernel density estimator for the density estimation of network-constrained point events, in this case MVCs, in a network space:

$$\lambda(z) = \sum_{i=1}^{n} \frac{1}{\tau} k\left(\frac{d_{iz}}{\tau}\right) \quad (1)$$

where $\lambda(z)$ is the density at location z, τ is the linear network search radius (bandwidth), $k(d_{iz}/\tau)$ is the weight of point i at distance d_{iz} to location z. The kernel function, k, is formed as a function of the ratio between d_{iz} and τ so that a distance decay effect can be taken into account in density estimation. This means that the further the distance between point i to location z, the less weight point i has in calculating density. Although there are several different kernel functions available to measure the distance decay effect, the impact of the choice of kernel is not significant whereas the choice of the search radius τ is important (Xie & Yan, 2008). This study uses the Quartic kernel, which when used in the network KDE function takes the form:

$$\lambda(z) = \sum_{i=1}^{n} \frac{1}{\tau}\left(\frac{3}{\pi}\left(1 - \frac{d_{iz}^2}{\tau^2}\right)\right) \quad (2)$$

Both the search radius (bandwidth) and kernel function are based on network distance instead of Euclidean distance and the density calculated is measured in linear units (Xie & Yan, 2008).

To implement network-based KDE, this study utilizes the R code written by Branion-Calles (2020) which was based on the method proposed by Xie and Yan (2008). In total, 80,671 lixels were created from 9,546 road segments as outlined in a prior section as the basis for the network KDE analysis. The center point for each lixel was found and the MVC point data was snapped to the nearest lixel center point, the total number of MVCs nearest to a lixel was counted and attributed to that lixel. Lixels that had one or more MVCs were defined as a source lixel, this was done to increase computational efficiency of subsequent processes.

A search radius (bandwidth) of 150m was used for the analysis, the distance value of 150m was deemed the most appropriate for identifying hotspots at a more local scale as larger search radii may mask some hotspot patterns (Xie & Yan, 2008). The shortest-path network distances from each source lixel's center point to its neighboring lixels' center points, within the search radius, were then calculated. From each source lixel's and its neighboring lixels' center points, a density value was calculated based on the Quartic kernel function, previously calculated network distance, and the number of MVCs that were attributed to the source lixel.

Xie and Yan (2008) also observed that the differences in kernel functions seem to be the least influential in the structure of density patterns in network KDE. If a lixel's center point is within the search radius of multiple source lixels, the density values from these source lixels were summed and assigned to that lixel. A density value of 0 was assigned to all other lixels. The network KDE values were calculated annually for MVCs that occurred in London, resulting in ten different KDE values for a given lixel, corresponding to each of the ten years in the study (2010-2019). The traffic volumes were used to normalize the network KDE values that were calculated, this is to control for the relationship that traffic volume has with MVC incidence as traffic volume is one of the most influential predictors when modeling MVCs (Lovegrove & Sayed, 2006; Levine et al., 1995; Gladhill & Monsere, 2012). After normalization, density values were multiplied by 1000 units of AADT. 1 unit of AADT means that on average, one vehicle traveled along a segment or through an intersection per day for the year the traffic volume data was collected. Therefore, this new value represents the density value per 1000 vehicles per day at that location. After the KDE values for all n = 80,671 lixels were computed, the lixels that were directly adjacent to an intersection were separated from lixels part of a mid-block road segment in order to perform separate analyses. This resulted in n = 63,976 lixels identified as being part of mid-block road segments and n = 16,695 lixels that were labelled as being part of the n = 5,301 intersections. The KDE values for lixels converging at an intersection were averaged and assigned to that intersection to further simplify analyses.

2.2.2.2 Trend Analysis & Hotspot Categorization

We performed a temporal trend analysis on the yearly KDE values for each lixel and intersection using linear regression. Multiple existing studies in MVC literature have used various forms of regression analysis to assess temporal trends of MVC data (Orsi et al., 2012; Ehsani et al., 2014; Schepers et al., 2017). The slope of the regression line of KDE against time (year) was analyzed to determine the relative trend of the KDE values for a given lixel or intersection. The direction of the slope indicates whether a lixel or intersection is experiencing increasing or decreasing rates of MVCs, while comparing the KDE values to the mean indicates the relative overall level of MVC occurrence at the lixel or intersection.

Assessing the trend of each lixel and intersection allows for the analysis of different types of hotspots. Hotspots that are increasing in relative MVC prevalence over time may have different built environment characteristics than a hotspot that is decreasing in MVC prevalence over time. Similarly, a hotspot that has been consistent and relatively high throughout the study period may also exhibit different characteristics.

Most studies analyzing hotspot trends have used ESRI's Emerging Hotspots Analysis tool in ArcGIS, which utilizes z-scores to assess the statistical significance of clusters and the Mann-Kendall statistic to assess the temporal trend of z-scores (Harris et al., 2017; Betty et al., 2020). While a popular tool for detecting hotspot trends, ESRI's tool uses Space-Time cubes as its medium for analysis making it difficult to apply to a network environment due to its lack of flexibility. However, there is no consensus definition or method of determining what constitutes a hotspot, with previous studies using various threshold values as benchmarks to select the relatively higher risk areas (Thakali et al., 2015; Bil et al., 2019). To distinguish each type of hotspot, this study uses the slope of the regression line and the mean KDE value of each lixel or intersection compared to their respective overall means and based on these two values, lixels and intersections were assigned to a category. This study looks at three main types of MVC hotspot trends: emerging, persistent, and diminishing, which are similar categories used in previous studies (Bil et al., 2019). Emerging hotspots, shown in orange in Figure 2-6, are hotspots that have relatively large positive coefficients, meaning they have higher network KDE values in recent years and moderate to high means, meaning they have relatively high network KDE values overall. Persistent hotspots, shown in red in Figure 2-6, are hotspots that have the greatest means, the highest network KDE values, and also have relatively stable slopes which indicate minimal fluctuation in yearly network KDE values. Diminishing hotspots, shown in yellow in Figure 2-6, are hotspots that have relatively large negative regression coefficients, meaning they had higher network KDE values in the earliest years of the study period and have lower network KDE values in recent years.

They also have moderate to high means which indicate a relatively high network KDE value overall. Baseline areas, shown as blue in Figure 2-6, are areas that have relatively stables slopes and relatively low means, indicating they have little fluctuation in network KDE values and have low network KDE values overall. The criteria for each category is shown in Table 2-3 and visualized in Figure 2-6. Emerging, persistent and diminishing hotspots were grouped together to determine the total amount of overall hotspots, whatever was not categorized as any of the three hotspot trend categories was deemed not a hotspot, or baseline. Examples of how lixel trends (Figure 2-7) and intersection trends (Figure 2-8) are assessed and categorized were mapped and compared.

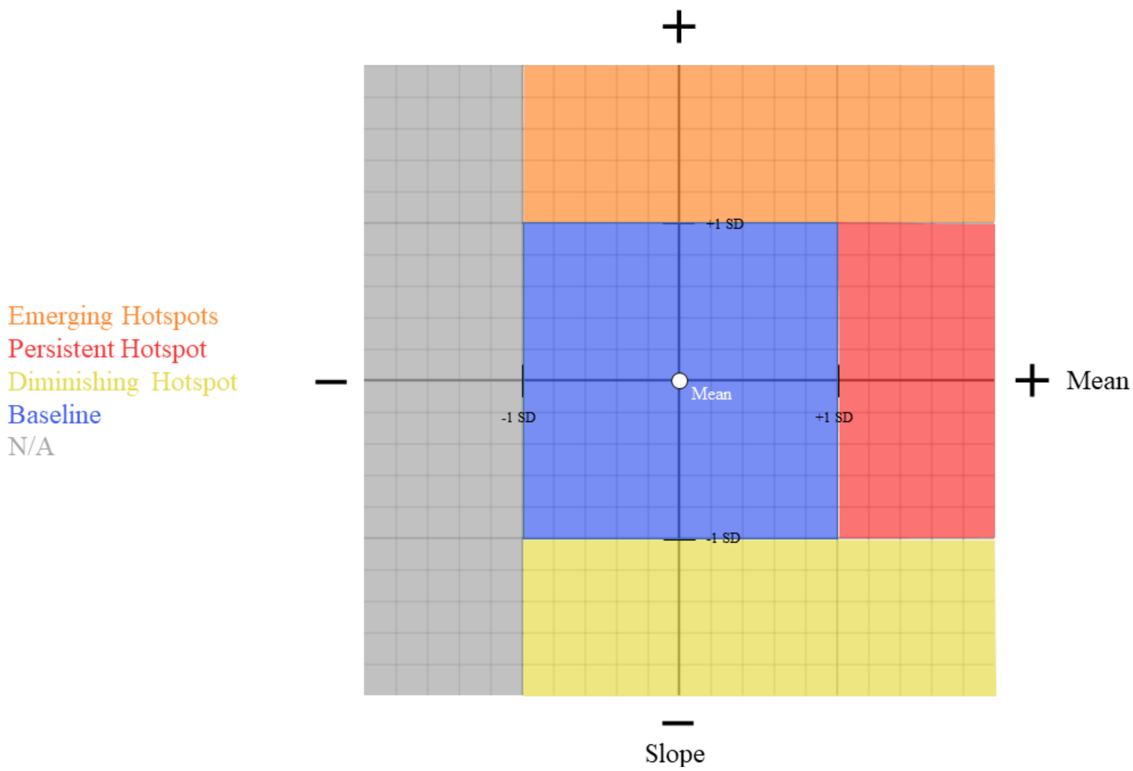

Figure 2-6: Hotspot categorization visualized, although not proportional this illustrates which areas of the distribution will be assigned to which category. The left side of the graph is greyed out as there were no lixels or intersections with a mean lower than one standard deviation less than the overall mean. The white dot represents the mean for both slope and mean overall.

Table 2-3: Hotspot categorization criteria used to determine the type of hotspot based on relative distribution. The criteria was applied to both lixels and intersections. The meaning of the abbreviations are as follows, s: Slope of a given lixel; S: Average slope of all lixels; m: Mean KDE of a given lixel; M: Mean KDE of all lixels; SD: Standard deviation.

Hotspot Type	**Overall Type**	**Relation to Overall Average Slope**	**Relation to Overall Mean**
Emerging	Hotspot	s > +1 SD	m > +1 SD
		s > +1 SD	M < m < +1 SD
		s > +1 SD	m < M
Persistent	Hotspot	-1 SD < s <S	m > +1 SD
		S < s < +1 SD	m > +1 SD
Diminishing	Hotspot	s < -1 SD	m < M
		s < -1 SD	M < m < +1 SD
		s < -1 SD	m > +1 SD
Baseline	Not a Hotspot	-1 SD < s <S	M < m < +1 SD
		-1 SD < s <S	m < M
		S < s < +1 SD	m < M
		S < s < +1 SD	M < m < +1 SD

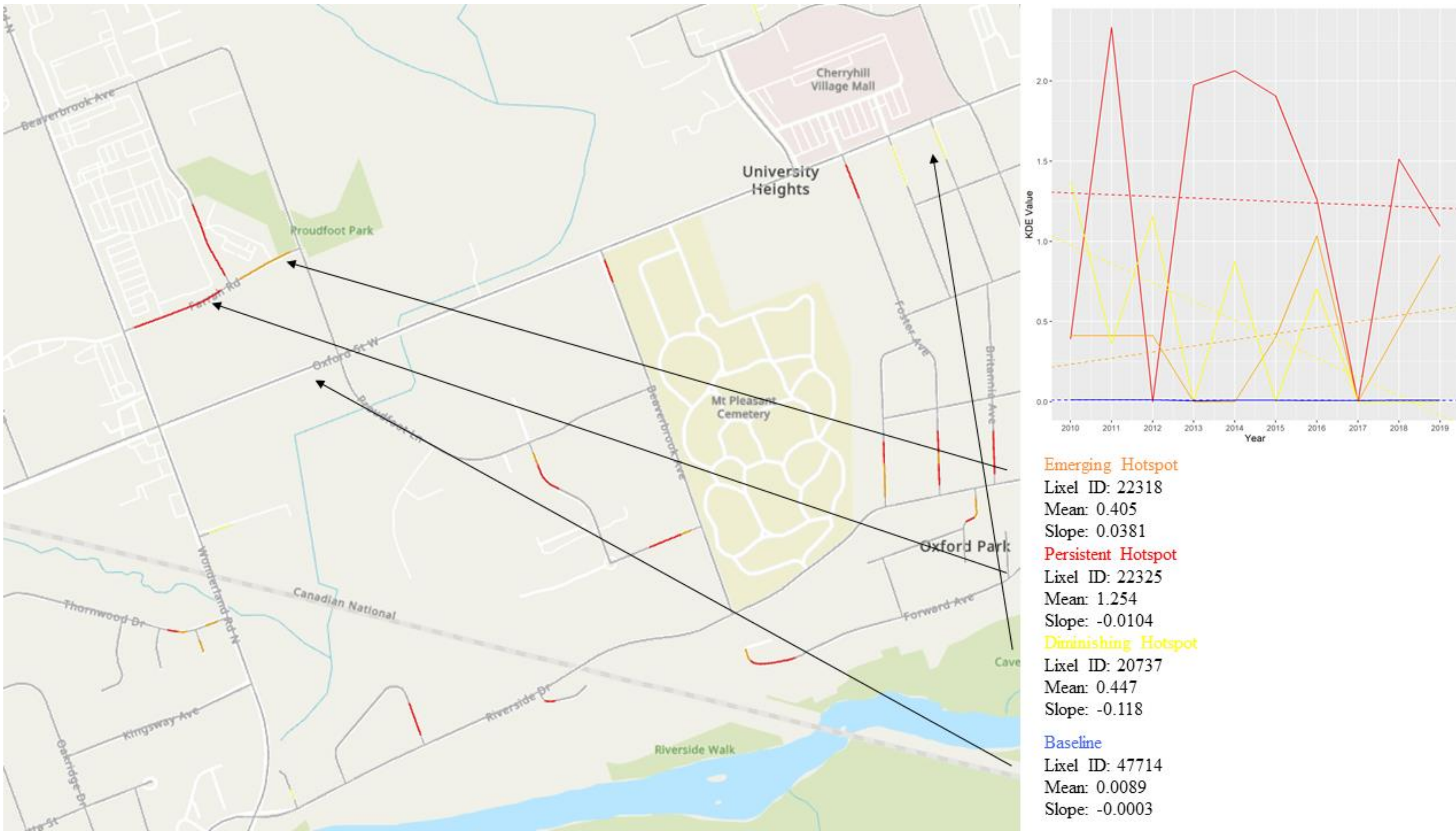

Figure 2-7: Examples of lixel hotspot trend lines and how they were subsequently categorized based on their slope and mean.

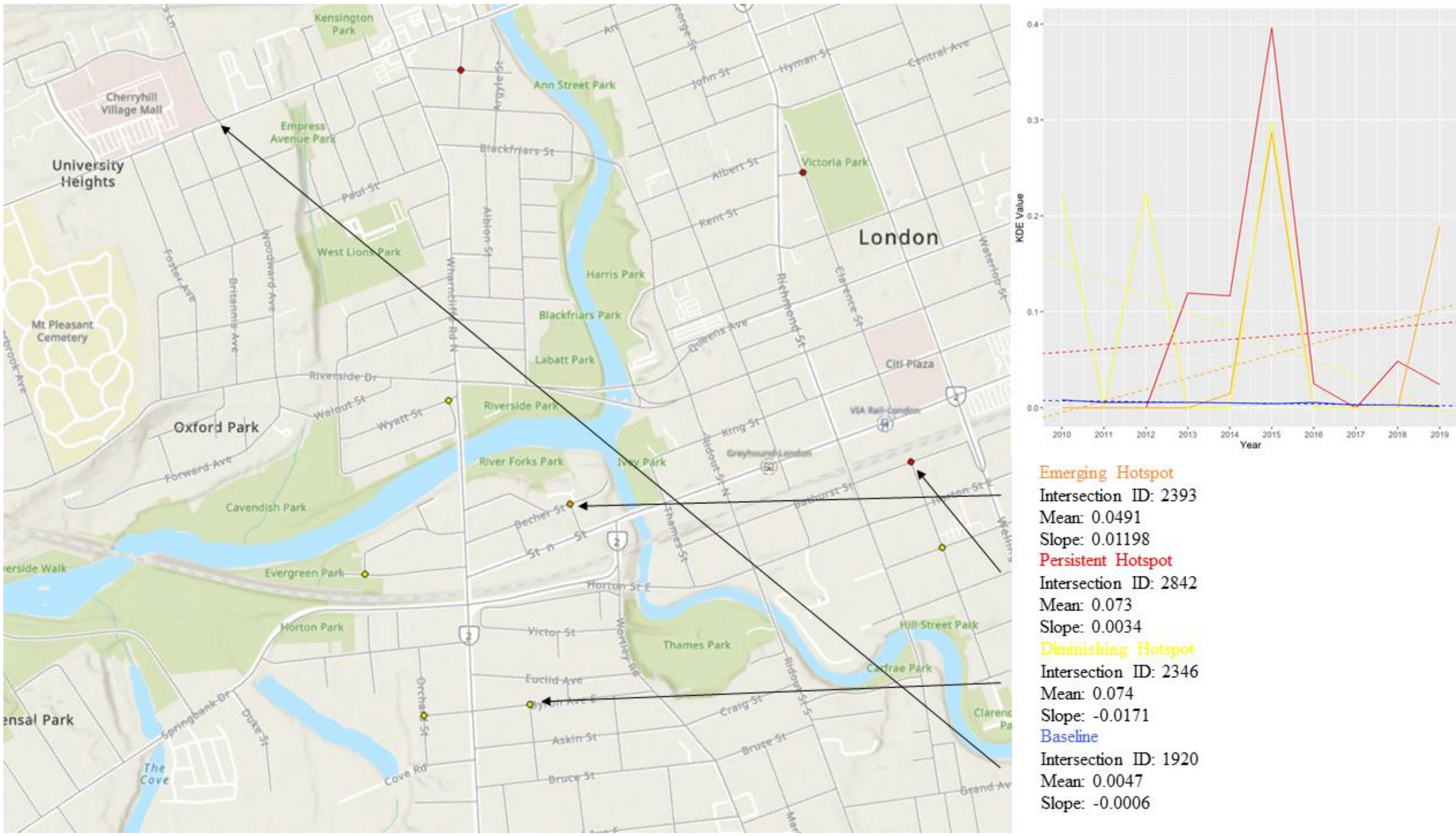

Figure 2-8: Examples of intersection hotspot trend lines and how they were subsequently categorized based on their slope and mean.

2.2.3 Statistical Analysis

Several studies have analyzed MVCs using logistic regression (Al-Ghamdi, 2002; Chen et al., 2012). Most studies test whether a collision resulted in a serious injury or fatality as the response variable for their model. This study uses whether a mid-block segment or intersection is classified as an MVC hotspot as the response variable for the first model. The use of hotspots as a response variable in a logistic regression has been used before in various applications of hotspot analysis, for example, in the comparison of spatial statistical methods for malaria hotspot detection (Mosha et al., 2014). This study also modeled the three types of MVC hotspots to see if relationships with variables differed with hotspot trends.

We fit logistic regression models with a number of environmental covariates to capture the nature of the surrounding built environment. The environmental variables used in the logistic regression models differed based on the relevancy of the variable to a mid-block or intersection collision (Table 2-2). The mid-block models included street lights, bike lanes, driveways, sidewalks, street trees, on-street parking, hedges and road width as its independent variables. The intersection models included street lights, bike lanes, sidewalks, street trees, hedges, average road width, signalized intersections and number of converging roads as its independent variables.

The goodness of fit of regression models was determined by computing McFadden's pseudo r-squared statistic for each model (Menard, 2000). All analyses were conducted using the R statistical computing environment, with some data processing and most mapping conducted in ArcGIS Pro. The script authored by Branion-Calles (2020) was used for the network KDE analysis, which utilizes the package stplanr for spatial network creation (Lovelace & Ellison, 2017) and DescTools for calculating McFadden's pseudo r-squared (Signorell, 2021).

2.3 Results

2.3.1 Network Kernel Density Estimation

Among 63,976 lixels, the mean network KDE value for a given year ranged from 0.016 to 0.031 and seems to be declining in recent years (Figure 2-9). This trend is similar to the downwards trend of fatal or injurious MVCs occurring annually in London. The annual mean network KDE values for the 5,301 intersections ranges from 0.0068 to 0.014 and also has a downward trend, albeit at a comparatively stable rate. The number of lixels with at least one MVC occurring on it seems to be relatively stable in comparison to the decline in MVC occurrence. This suggests there are less collisions happening overall, but MVCs may be persisting at the same locations, which would result in lower network KDE values, potentially explaining the decline in mean network KDE values.

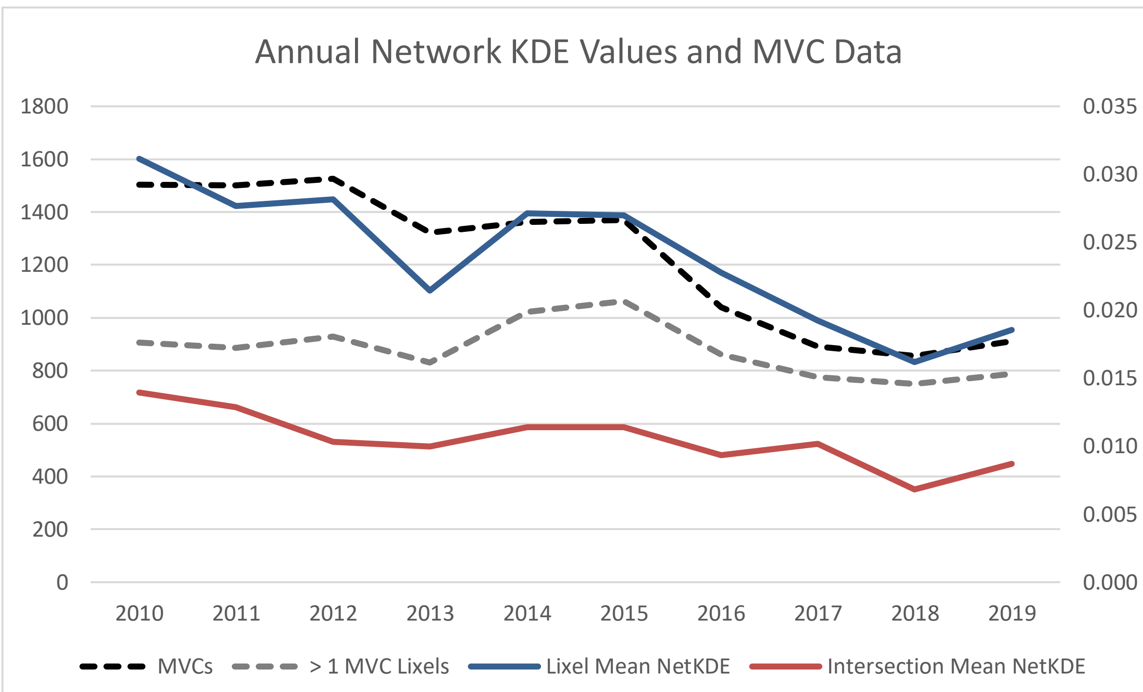

Figure 2-9: Mean network KDE values per 1000 AADT are shown for lixels (solid blue) and intersections (solid orange). The overall number of fatal or injurious MVCs are shown in dashed black and lixels that have at least one MVC are shown in dashed grey. The y-axis for the dashed lines is on the left, while the y-axis for the solid lines is on the right.

2.3.2 Trend Analysis

The average slope for lixels without true zero lixels (n = 36,333), lixels with a density value of zero, was -0.0033 (SD: 0.046). This indicates that overall, network KDE values for road segments in London are slightly decreasing. The average mean for all MVC containing lixels for the entire study period was 0.055 (SD: 0.258). The distribution of these two metrics are shown in (Figure 2-10). The histogram for the slope of lixels shows most lixels have a slope close to 0 and they tend to be slightly negative. The negative mean for lixel slopes, considering the distribution, indicates there are several lixels that have significantly negative slopes. The histogram for the mean of all lixels is shown with a log^{10} scale transformation, showing many lixels have a mean KDE between 0.001 and 0.01.

The average slope for intersections without true zero intersections (n = 2,152), was -0.0009 (SD: 0.013), which indicates intersections are also demonstrating decreasing KDE values over time, but at a slower rate than lixels. The average mean for intersections without true zero intersections was 0.0177 (SD: 0.069). The distribution of these two metrics without true zero intersections are shown in (Figure 2-11). The histogram for the average slope of intersections shows most intersections have a slope close to 0 and they tend to be negative. The mean for intersection slopes seems to be much more in line with the distribution, indicating less outliers than lixels. The histogram for the mean of all intersections is shown with a log^{10} scale transformation, and also show most intersections fall between a mean KDE of 0.001 and 0.01.

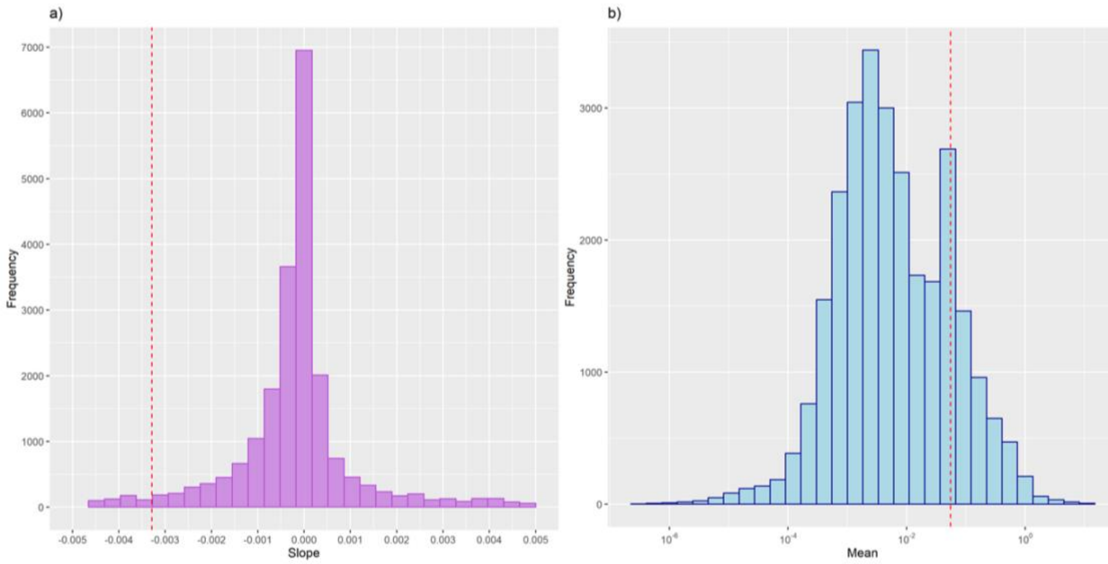

Figure 2-10: Histograms showing the distribution of (a) slope excluding lixels exceeding plot limits (n = 6,577) and (b) KDE mean for all MVC lixels (n = 63,976). A $\log_{10}$ scale transformation is used for the x-axis. The mean of both distributions is shown as a vertical, dashed red line.

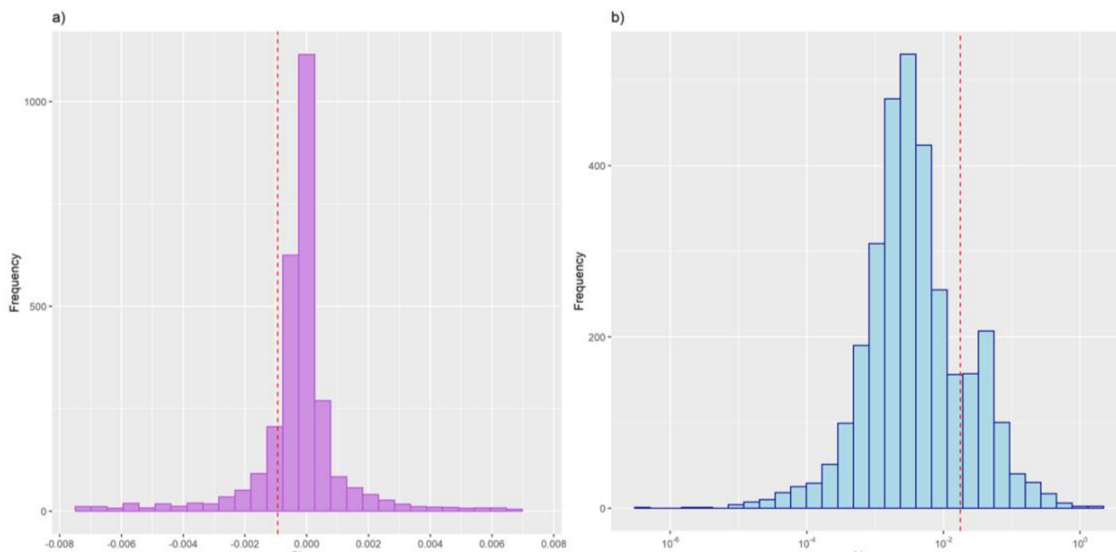

Figure 2-11: Histograms showing the distribution of (a) slope excluding intersections exceeding plot limits (n = 341) and (b) KDE mean for all MVC intersections (n = 5,301). A $\log_{10}$ scale transformation is used for the x-axis. The mean of both distributions is shown as a vertical, dashed red line.

2.3.3 Hotspot Categorization

Of the 63,976 lixels, 2,328 (3.64%) were classified as hotspots and 61,648 were classified as baseline lixels. Of the 2,328 hotspots, 548 (23.5%) were classified as emerging hotspots, 628 (27%) were classified as persistent hotspots and 1,152 (49.5%) were classified as diminishing hotspots (Figure 2-12a). After mapping these lixel hotspots, they are observed to be generally distributed along road segments adjacent to major roads (Figure 2-13).

Of the 5,301 intersections, 308 (5.81%) were classified as hotspots and 4,993 were classified as baseline intersections. Of the 308 hotspots, 110 (35.7%) were classified as emerging hotspots, 57 (18.5%) were classified as persistent hotspots and 141 (45.8%) were classified as diminishing hotspots (Figure 2-12b). After mapping these intersection hotspots, they seem to be concentrated in the eastern part of central London (Figure 2-14).

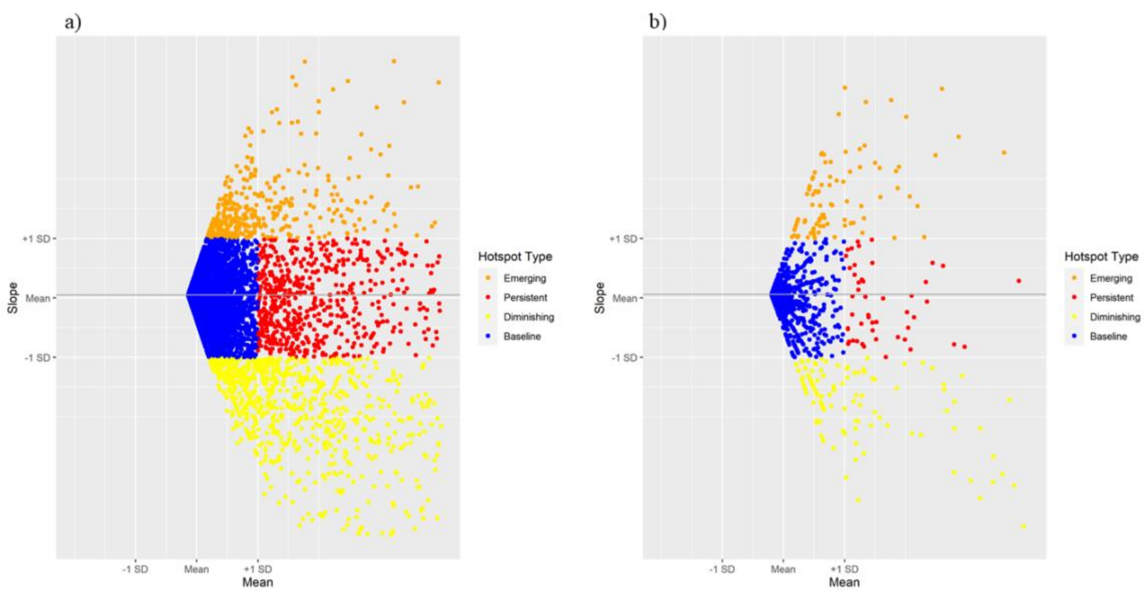

Figure 2-12: a) All lixels (n = 63,976) plotted according to their slope and mean values, colored according to their hotspot category. Lixels that exceeded the limits of the plot are not shown (n = 399). b) All intersections (n = 5,301) plotted according to their slope and mean values, colored according to their hotspot category. Intersections that exceeded the limits of the plot are not shown (n = 43).

Figure 2-13: A map showing the distribution of hotspot types throughout lixels in London, Ontario.

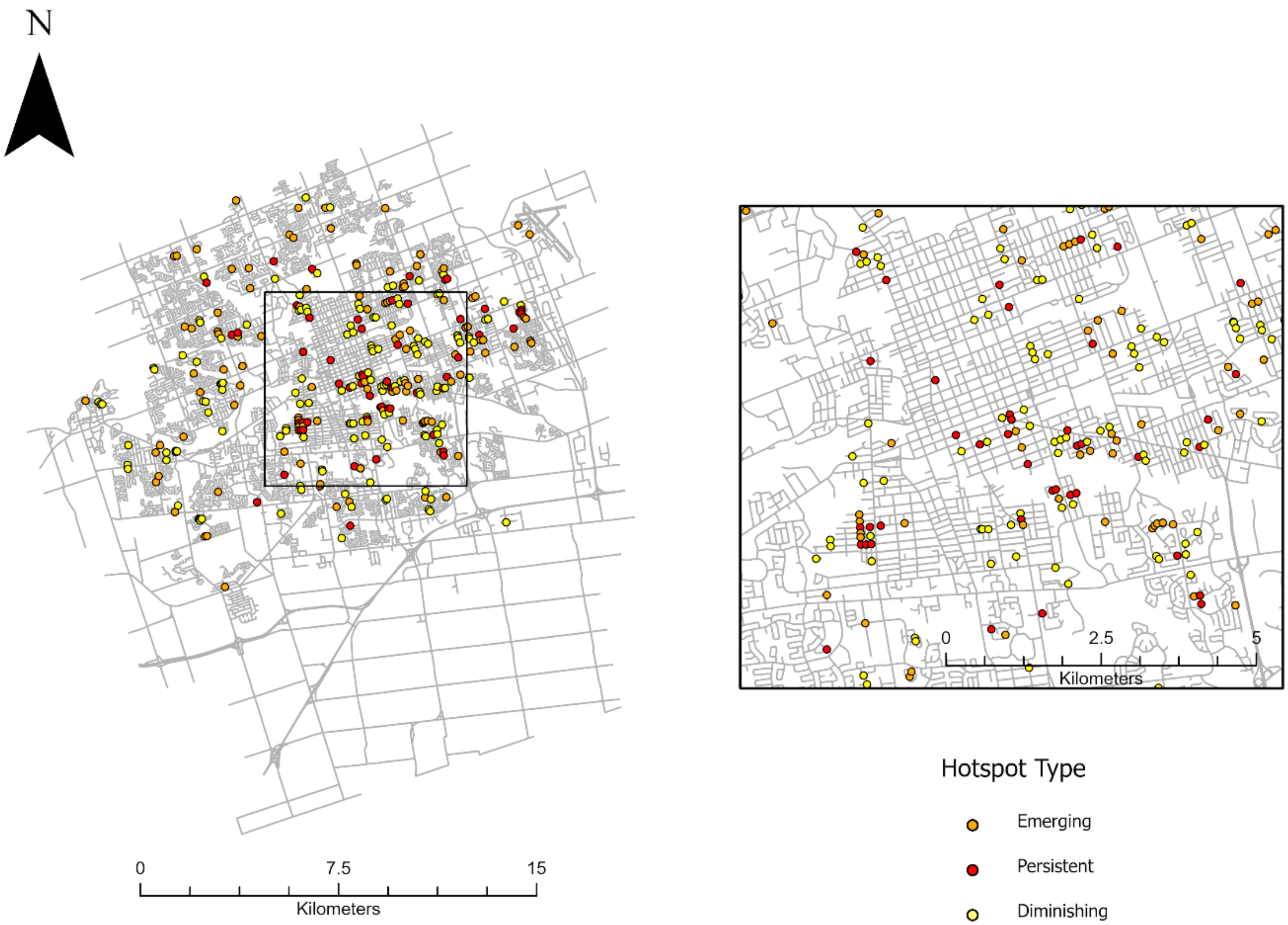

Figure 2-14: A map showing the distribution of hotspot types throughout intersections in London, Ontario.

2.3.4 Statistical Analysis

All mid-block (i.e. lixel) models showed a statistically significant positive relationship between street lights and MVC hotspots with mid-block segments that have street light presence being approximately twice as likely to be a hotspot as those without. However, in all intersection models, street lights showed no significant relationship with hotspots.

Bike lanes have a statistically significant negative relationship with MVC hotspots at mid-block locations where segments with bike lanes were found to be on average 35% lower chance of being an MVC hotspot, with a greater effect on emerging hotspots (64% lower chance). Bike lanes also show a significant negative association with overall hotspots (56% lower chance) and similarly has a much greater effect on emerging hotspots (92% lower chance). Persistent hotspots and diminishing hotspots were not found to have a statistically significant relationship with bike lanes at intersections.

Hedges were found to have a statistically significant association with all models except for emerging and persistent hotspots at intersections. Mid-block segments with hedges had an average 34% higher likelihood of being an MVC hotspot, while intersections experienced a similar effect (54% higher chance). Diminishing hotspots at intersections experienced a particularly great additive effect from hedges (96% higher chance).

All mid-block models showed no statistically significant relationship between driveways and MVC hotspots except with emerging hotspots. On average, every driveway on a mid-block segment contributed a 1% lower likelihood of being an emerging hotspot.

Sidewalks have a statistically significant positive relationship with all hotspots at mid-block locations, having the greatest effect on persistent hotspots. Segments with a sidewalk were four times as likely to be a MVC hotspot and six times as likely to be a persistent hotspot. All intersection models did not have a significant association with sidewalks.

All hotspots at mid-block segments have been found to have a statistically significant association with street trees, with every street tree on a segment decreasing the chance of a MVC hotspot by 3%. Hotspots at intersections were not found to have a significant association with street trees.

On-street parking was found to have a significant positive effect on all hotspots at mid-block locations, with segments being four times as probable of being a MVC hotspot.

Compared to medium roads, narrow roads were found to have a significant, slight positive association (26% higher chance) with persistent hotspots at mid-block segments. Narrower roads did not have any significant effect on other hotspot types at mid-block locations or intersections. Wider roads were found to have a significant negative effect (over 80% lower likelihoods) on all hotspot types at mid-block segments and intersections except on emerging and persistent hotspots at intersections.

Traffic signals were found to have no statistically significant effect on hotspots overall at intersections.

Simpler intersections, intersections with three or fewer roads converging at an intersection, had a significant reductive effect (40% lower chance) on all hotspot types except emerging hotspots in comparison to normal intersections, intersections with four converging roads. Complex intersections with five or more converging roads did not have any significant association with MVC hotspots.

2.3.4.1 Model Fit

Overall, the mid-block models had slightly higher McFadden’s R^2 coefficients, which indicates slightly better model fits than the intersection models. The McFadden R^2 values ranged from 0.041 to 0.089. The model with the highest R^2 coefficient was the persistent mid-block hotspot model. The emerging mid-block hotspot model had the lowest R^2 value. It should also be noted that few coefficients in the intersection models were statistically significant.

Table 2-4: Results from logistic regression of hotspots against baseline for n = 63,976 lixels in London, Ontario, Canada. Estimated coefficients (β), estimated coefficient exponents (exp(β)), estimated standard error (S.E.) and p-value (p) for each model are reported along with McFadden's R^2 value. A "*" denotes a p-value lower than 0.05, a "." denotes a p-value greater than 0.05.

	Overall Hotspot Regression				Emerging Hotspot Regression				Persistent Hotspot Regression				Diminishing Hotspot Regression			
Variable	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*
Street Lights	0.786	2.195	0.092	*	0.529	1.697	0.157	*	1.106	3.023	0.205	*	0.822	2.276	0.137	*
Bike Lanes	-0.430	0.650	0.079	*	-1.021	0.360	0.208	*	-0.426	0.653	0.145	*	-0.264	0.768	0.103	*
Hedges	0.295	1.343	0.047	*	0.350	1.419	0.096	*	0.267	1.306	0.087	*	0.288	1.334	0.065	*
Driveways	-0.001	0.999	0.002	.	-0.012	0.988	0.004	*	0.003	1.003	0.003	.	0.002	1.002	0.003	.
Sidewalks	1.417	4.125	0.075	*	1.044	2.841	0.133	*	1.820	6.171	0.161	*	1.456	4.287	0.110	*
Trees	-0.032	0.969	0.003	*	-0.021	0.979	0.006	*	-0.049	0.952	0.006	*	-0.028	0.973	0.004	*
Parking	1.405	4.076	0.125	*	0.941	2.563	0.318	*	1.445	4.243	0.211	*	1.541	4.670	0.159	*
Medium Road	(REF)															
Narrow Road	0.008	1.008	0.062	.	-0.069	0.933	0.121	.	0.234	1.264	0.111	*	-0.080	0.923	0.091	.
Wide Road	-1.953	0.142	0.147	*	-1.766	0.171	0.301	*	-2.209	0.110	0.300	*	-1.903	0.149	0.202	*
McFadden's R^2	0.082				0.041				0.089				0.078			

Table 2-5: Results from logistic regression of hotspots against baseline for n = 5,301 intersections in London, Ontario, Canada. Estimated coefficients (β), estimated coefficient exponents (exp(β)), estimated standard error (S.E.) and p-value (p) for each model are reported along with McFadden's R^2 value. A "*" denotes a p-value lower than 0.05, a "." denotes a p-value greater than 0.05.

	Overall Hotspot Regression				Emerging Hotspot Regression				Persistent Hotspot Regression				Diminishing Hotspot Regression			
Variable	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*	β	exp(β)	S.E.	*p*
Street Lights	0.439	1.551	0.239	.	0.723	2.061	0.423	.	0.527	1.695	0.565	.	0.220	1.246	0.329	.
Bike Lanes	-0.812	0.444	0.251	*	-2.637	0.072	1.008	*	-0.531	0.588	0.480	.	-0.406	0.666	0.312	.
Hedges	0.433	1.542	0.123	*	0.190	1.209	0.198	.	0.372	1.451	0.278	.	0.670	1.955	0.181	*
Sidewalks	0.227	1.255	0.181	.	0.221	1.247	0.294	.	0.223	1.250	0.412	.	0.235	1.265	0.266	.
Trees	0.004	1.004	0.018	.	0.029	1.029	0.018	.	-0.028	0.972	0.028	.	-0.006	0.994	0.017	.
Signalized	-14.72	0.000	332.0	.	-14.497	0.000	784.6	.	-15.94	0.000	937.2	.	-14.06	0.000	331.2	.
Medium Road Avg	(REF)															
Narrow Road Avg	-0.323	0.724	0.335	.	-0.239	0.788	0.522	.	-16.03	0.000	1124	.	-0.002	0.998	0.433	.
Wide Road Avg	-1.915	0.147	0.461	*	-15.951	0.000	577.4	.	-1.007	0.365	0.619	.	-2.138	0.118	0.723	*
Normal Intersection	(REF)															
Simple Intersection	-0.508	0.602	0.150	*	-0.539	0.583	0.271	.	-0.727	0.483	0.308	*	-0.631	0.532	0.21	*
Complex Intersection	-13.23	0.000	259.4	.	-0.194	0.824	7331	.	-14.96	0.000	7081	.	-12.24	0.000	2596	.
McFadden's R^2	0.058				0.069				0.044				0.053			

2.4 Discussion

2.4.1 Built Environment Influences

2.4.1.1 Bike Lanes

The mid-block segment models suggest that there is a negative relationship between MVC hotspots and the presence of bike lanes, which is consistent with existing MVC literature. The quality of bike lanes, that is the degree to which the bike lane is separated and cyclist is protected from traffic, has been shown to have an influence on MVCs involving cyclists (Reynolds et al., 2009). Bike lanes that are merely painted lines on the road surface have a lesser negative influence on MVCs than a bike lane that has a physical barrier between motor vehicle traffic and the cyclist (Reynolds et al., 2009). Bike lanes not only protect cyclists but also protect pedestrians by providing a buffer between the sidewalk (or curb in the case where there is no sidewalk) and traffic. Similarly, better quality bikes lanes will likely have a greater influence on reducing pedestrian MVCs. Bike lanes have also been shown to have an effect on drivers as well. The presence of bike lanes is thought to create a narrowing effect on roads that can influence drivers to exercise more caution (Reynolds et al., 2009). The results of the mid-block models seem to corroborate the findings of previous studies, showing that in the London context bike lanes have a negative effect on MVC hotspots especially along mid-block segments.

The intersection models exhibit similar effects, but are not statistically significant. This may be a result of the intersection models as a whole, however bike lanes at intersections have also been shown to have potentially increasing effects on MVCs (Reynolds et al., 2009). The presence of bike lanes encourages more cyclists to use the available facilities on those roads, which can create opportunities for conflicts between motor vehicles and cyclists.

The results show that bike lanes seem to have an especially negative effect on emerging hotspots at both intersections and mid-block segments. This may be a result of the construction of bike lanes following London’s 2016 Cycling Master Plan which proposed

68km (41.7% increase) of on-street bike lanes to be constructed over the course of the next five years (City of London, 2016). This suggests that the areas these bike lanes are being built are not emerging hotspots. These areas potentially could have been emerging hotspots may have been dampened by the installation of bike lanes in recent years and have either declined or plateaued in terms of their network KDE value. The availability of the geographic data of bike lane types in London could allow for the evaluation of the relationship between bike lane quality and MVCs in the London context.

2.4.1.2 Street Lights

The consensus in MVC literature is that road visibility has a significant influence on MVC incidence (Retting et al., 2003; Stoker et al., 2015; Ewing & Dumbaugh, 2009). In particular, street lighting plays an important role in reducing MVCs occurring in the evening or at night, especially those involving pedestrians and cyclists. It is harder to see pedestrians and cyclists at night compared to vehicles which usually have head/tail lights. The results of this study seem to contradict these existing findings with all mid-block models showing street lights have a significant positive effect on MVC hotspots. The intersection models also show positive effects, but are not significant. However, there may be potential explanations for this contradiction. First, most of London's roads and intersections are well-lit (68%) and all main roads and intersections have several street lights. The vast majority of MVCs resulting in injury or fatality are found in areas around main roads and intersections, areas that tend to have more vehicles, pedestrians and cyclists, so it makes sense that the models are showing an association between street lights and MVCs. Another potential explanation is that areas without street lights also may be a deterrent to pedestrians and cyclists, choosing not to travel along those roads. This study also does not differentiate between MVCs occurring during the day and MVCs occurring at night, so it is difficult to ascertain the effect that street lights actually have on MVCs in London.

2.4.1.3 Hedges

Another aspect of road visibility that has an influence on MVC incidence is sightlines, particularly at intersections (Dumbaugh & King, 2018). If road users are unable to see each other in time due to objects obstructing their view it reduces the time that they have to react, creating dangerous situations. For example, a driver may not see another vehicle trying to cross the intersection at speed or a pedestrian that is about to run across the road. This study looks at hedges near roads as an object that has an impact on sightlines. The results of this study are consistent with existing literature and show that hedges do have a significant positive effect on MVC hotspots at mid-block segments and intersections. While it is clearer to see the impact poorly placed hedges can have at intersections, it is less obvious why hedges are associated with MVCs at mid-block segments. However, hedges along mid-block segments can obstruct the vision around driveways creating hazardous situations similar to that of intersections with poor sightlines. This may be a partial explanation as to why hedges are associated with MVCs at mid-block segments. The issue with sightlines at intersections has been recognized by the City of London and mentioned briefly in their Complete Streets Design Manual (2018). However, they only mention a loose guideline for future streets, lacking specification in terms of recommended distances from intersections, types of sightline obstruction and do not mention a plan for existing streets (City of London, 2018). The focus also remains on the removal of sightline obstructions, however, according to the Transport Association of Canada (2011), the speed of the vehicle greatly influences the sight distance needed. That is, the faster a vehicle is moving the greater distance from an intersection a driver needs to be able to have an unobstructed view of incoming traffic. In addition to the removal of sightline obstructions, there should be consideration on decreasing vehicle speeds in order to make the approach to intersections safer. There is no mention of addressing sightlines along mid-block segments, particularly driveways. While it is positive that London is addressing the issue with sightlines at intersections, this study shows it is important to consider mid-block segments as well.

2.4.1.4 On-Street Parking

All mid-block models show that on-street parking has a significant positive effect on MVC hotspots at mid-block segments. The literature on on-street parking does not seem to agree on its definitive effect on MVCs, while they have been shown to have potential as having a traffic calming effect, other studies suggest on-street parking may obstruct sightlines (Ewing & Dumbaugh, 2009; Retting et al., 2003). In the London context, on-street parking seems to corroborate the latter. This is concerning as London's Complete Streets Design Manual mentions on-street parking as a positive feature citing its many benefits including its traffic calming and street revitalization potentials (2018). If not executed correctly and with care, on-street parking may have dangerous effects on London streets. Studies have mentioned positioning on-street parking at an angle instead of parallel to streets, thereby improving sightlines (Retting et al., 2003). Regardless of the approach that London chooses to use, on-street parking should be implemented with care and intention.

The particularly positive relationship with on-street parking and diminishing hotspots could be explained by recent decreases in activity in and around downtown London. Similar to sidewalks, a majority of on-street parking facilities are located in downtown London. With more people favoring the suburban malls closest to them, due to the convenience of their private vehicles and the massive swathes of surface parking, there has been a decrease in traffic in downtown London.

2.4.1.5 Sidewalks

The presence of sidewalks in London seem to be significantly associated with MVC hotspots, particularly at mid-block segments. This may seem to contradict literature that indicate sidewalks tend to be safer for pedestrians than roads without a sidewalk (Ewing & Dumbaugh, 2009). However, the presence of sidewalks can also increase the pedestrian volume for that road, thereby increasing the exposure of pedestrians to vehicles. This likely explains the positive association between sidewalks and MVC hotspots in London. Persistent hotspots in particular experience an especially strong positive association with sidewalk presence. This is a concerning outcome, especially with the recent advocacy of active travel and physical exercise. These results show that there has been a lack of safety measures in place for the most vulnerable of road users in London. This is addressed in the 2018 Complete Streets Design Manual, recommending adequate sidewalk widths, street side elements and buffers depending on the street classification. While the construction of sidewalks is positive in terms of pedestrian accessibility and connectivity, it does not necessarily directly translate the walkability of an area. It is just as important to create a safe and walkable environment around the sidewalk as it is to construct a sidewalk. On-street parking and bike lanes can act as buffers between pedestrians and vehicular traffic, reducing exposure. Street side elements like street trees, planters and benches can act as both traffic calming objects and physical barriers to protect pedestrians. While the feasibility of installing these safety measures will depend on the street classification and expected pedestrian volume, it is an important consideration in the revitalization and regeneration efforts of the City.

It is difficult to discern why sidewalks seem to have a strong positive effect on diminishing hotspots, however it could be explained by lower pedestrian volumes in recent years. Downtown London has been experiencing difficulties with attracting shoppers, restaurant goers and the general population, losing patrons to suburban malls like Masonville Mall or White Oaks Mall, and neighborhood strip malls. A large portion of London's sidewalks are located in the downtown, and with less pedestrian exposure, this could explain why some hotspots are diminishing.

2.4.1.6 Street Trees

London's Complete Streets Design Manual considers street trees quite carefully, outlining characteristics for an ideal street tree and where they should be located in road design (2018). Street trees are not only a valuable environmental resource, but can influence the walkability or commercial viability of an area (Naderi, 2003). Additionally, in a road safety context, street trees are a common example of a street side object. If placed appropriately, street trees, along with the grassy medians they are often planted on, can act as a buffer and barrier between pedestrians and vehicular traffic (Naderi, 2003). Street trees also have a traffic calming effect, creating a narrowing perception for drivers by establishing a hard edge. The mid-block models in this study show a significant negative association between street trees and MVC hotspots. This is consistent with existing literature and shows that the City of London should continue in its efforts in planting and maintaining well-designed treescapes.

2.4.1.7 Road Width

Narrow roads have been associated with lower MVC incidence in much of the existing planning literature (Ewing & Dumbaugh, 2009; Stoker et al., 2015; Retting et al., 2003). The rationale is that a narrow road creates a constrictive effect on drivers, influencing them to drive with more care and caution, thereby reducing MVCs (Ewing & Dumbaugh, 2009). The results of the persistent hotspot model at mid-block segments seem to contradict this existing theory, with narrow roads being positively associated with persistent MVC hotspots in London. It is difficult to discern why this is the case, however the association could be explained by the potential lack of traffic calming or street side protection at these locations. Narrow roads alone may not have enough of a traffic calming effect and may also require elements like speed humps, street trees and bike lanes to ensure a safe street. These narrow segments could also be a persistent problem due to inappropriate design speeds. The way a road is designed will influence actual operating speed rather than the posted speed limit (Dumbaugh & King, 2018). As such, if road segments are not designed appropriately, they could lead to operating speeds not safe for the road environment. For example, the approach to a sharp bend in a road should be designed to slow vehicles down, especially with narrow road segments as there is less room for error. Narrow road widths should be used in addition with further traffic calming and street side protection measures to reduce MVCs. Conventional engineering practice, however, has sought to give drivers as much room for error as possible with wider lanes and roads (Ewing & Dumbaugh, 2009; Dumbaugh & King, 2018). However, this may cause drivers to drive with less care and often at greater speeds, resulting in more severe accidents. The results of this study seem to contradict this theory as wider roads are significantly negatively associated with MVC hotspots in London at both intersections and mid-block segments. The method used to calculate road width likely includes bike lanes as a majority of the bike lanes in London are adjacent to and on the same surface as the road (City of London, 2016). This may explain some of the negative association between wide roads and MVCs, however the wide road coefficient has a greater magnitude than the bike lane coefficient, suggesting that bike lanes are not the sole reason for this negative association. The negative association with wider roads could also be a result of the normalization process, as the wider roads likely have significantly greater traffic volumes than normal roads. This would mean wider roads have smaller network KDE values, resulting in their likely classification as a baseline area.

2.4.1.8 Intersection Complexity

This study found that simple intersections, intersections with three converging roads, are less likely to be an MVC hotspot than normal intersections, intersections with four converging roads. This is consistent with existing literature which suggests that three road intersections are safer than four road intersections as the number of conflict points decrease dramatically at three road intersections (Dumbaugh & Li, 2010; Miranda-Moreno et al., 2011). With less opportunities for conflicts, road users need to process less information in order to make a correct decision. This study did not consider roundabouts as an intersection type, however the potential they have in reducing conflict points has been well documented in the literature, particularly at small to medium sizes (Ewing & Dumbaugh, 2009; Retting et al., 2003). The Complete Streets Design Manual does briefly mention guidelines for a roundabout, but a complex, large roundabout. These large roundabouts present some accessibility challenges, especially for pedestrians or cyclists which may make for riskier areas (Ewing & Dumbaugh, 2009). It would be beneficial for the City to consider small or medium sized roundabouts at primary or secondary collectors as the accessibility challenges are not as substantial at smaller scales.

2.4.1.9 Signalized Intersections

Although not statistically significant, signalized intersections are negatively associated with MVC hotspots overall in London, this corroborates existing literature (Dumbaugh & King, 2018). Typically, signalized intersections are located at intersections that require intersection control because of the volume and complexity of road users. In these cases, signalized intersections are especially effective in temporally separating vehicles, pedestrians and cyclists. It is important to prioritize which intersections traffic signals should be installed at, as it is not feasible to install traffic signals at every intersection. The Complete Streets Design Manual emphasizes the need for traffic signals at four road intersections that have cycling facilities (2018). The construction of small to medium sized roundabouts could potentially reduce the installation and maintenance costs of a signalized intersection while still making the intersection safer.

2.4.2 Limitations

One of the main limitations of this study is its reliance on police records for MVC data. Issues with unreliability and under-reporting have been well documented in previous MVC literature (Amoros et al., 2006; Janstrup et al., 2016; Watson et al., 2015). Typically, these unreported MVCs do not involve injuries or fatalities and therefore likely would have been excluded from this study. Future MVC research would benefit from improvements in MVC data collection and links to hospital emergency room data.

Another limitation is the lack of temporal data for built environment variables. It is difficult to determine the cause of some MVC hotspot trends as the available built environment data is static. The ability to track how the built environment is changing along with how MVC locations are changing could lead to even more robust interpretations and conclusions.

The nature of network KDE means it smooths MVC data over adjacent lixels, converting MVCs from a point event to lixels with a distribution of risk (Xie & Yan, 2013). This means lixels next to areas with high MVC occurrence, major intersections for example, will have relatively high network KDE values despite MVCs not necessarily occurring directly on the lixel. While this may seem like an overestimation, it is important to consider areas surrounding intersections with high MVC occurrence as typically characteristics of the surrounding areas also have a role in influencing MVCs. These areas may not necessarily have MVCs occurring on them, but are still risky areas.

Another issue with KDE is the lack of statistical significance in the estimation process and designated hotspot density threshold (Xie & Yan, 2008). Previous studies have indicated the overall lack of consensus in hotspot definition, usually resorting to an arbitrary selection method to determine the hottest areas or highest values (Thakali et al., 2015; Bil et al., 2019). The method this study uses for hotspot categorization is based on previous studies' utilization of linear regression trend analysis (Orsi et al., 2012; Ehsani et al., 2014; Schepers et al., 2017) and relative distribution to define the hotspot categories. The calculated network KDE values were used as the basis for hotspot identification and subsequent logistic regression, thereby adding a layer of statistical significance to the results and mitigating the lack of statistical rigor associated with network KDE.

2.4.3 Future Considerations

While the network-based KDE seems to be the most appropriate approach in the identification of MVC hotspots, it would be interesting to see how the results would change if certain parameters were changed, specifically lixel length and search bandwidth. If the maximum lixel length was shortened from 25m to around 15-20m, the spatial pattern of the resulting density values would likely be more pronounced and more accurately display local variation. Decreasing the search bandwidth from 150m to 100m would have a similar effect, emphasizing hotspot patterns and locations with more detail. Using these smaller and more detailed hotspots in this analysis will in turn increase the detail in terms of built environment lixelization and subsequent modeling. While it is unknown how results may change, it is known that an increase in granularity will increase the computational load.

The buffer distances used to attribute built environment variables to lixels and intersections could have also been improved. The buffer distance should be large enough to encompass all relevant built environment features but should also not encroach into the area of another lixel or intersection. The size of an intersection or road segment will influence how large a buffer should be, which means the buffer size will vary. This study attempts to find a buffer distance that suits lixels and intersections overall, but it would be interesting to see how results might change if the buffer distance was dynamic.

2.5 Conclusion

This study has resulted in several key findings that have implications on road safety in London, ON and its Vision Zero goal. Firstly, bike lanes have emerged as a significant negative influence on fatal and injurious MVCs. The City's recent investment in bike lanes is a positive sign, however the construction of better quality, more separated bike lanes is encouraged not only for the safety of cyclists, but pedestrians as well. The finding that sidewalks have a significant positive association with MVC hotspots is a worrying revelation. The promotion of walking necessitates a safe environment for pedestrians, not just the construction of a platform on which to walk. There is a need for the City to invest in its pedestrian infrastructure, particularly on safety measures like street side buffers and crossing aids like street islands and signalized intersections. Obstructions to sightlines like on-street parking and hedges have also been found to have a significant positive influence on MVC hotspots. However, this does not indicate a need for the removal of these features, rather a more nuanced approach in the implementation of these features. Future policy and road design practice should exercise caution in the implementation of these features and should consider a holistic approach for the safety of all road users.

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Chapter 3

3 Estimating the Pedestrian Volume of Students Commuting to School and Evaluating Safety Measures in London, Ontario.

3.1 Introduction

Motor vehicle collisions (MVCs) are the eighth leading cause of death for people of all ages, and the leading cause of death for children and young adults (5-29 years) (World Health Organization, 2018). Much of the current child MVC research has focused on child passengers involved in MVCs (Brolin et al., 2014; Durbin et al., 2005) and child pedestrian MVCs (Cloutier et al., 2021; Rothman et al., 2014; Connelly et al., 1998; Schwebel et al., 2012; Stevenson et al., 2015). Children are especially vulnerable to pedestrian MVC occurrence because of their limited experience and developmental capacity to perceive and understand traffic hazards (Schwebel et al., 2012; Cloutier et al., 2021). Studies have shown that children, especially younger children, are typically unable to judge vehicle speeds and make safe decisions when crossing roads (Connelly et al., 1998). They are also more vulnerable to severe injuries and fatalities resulting from MVCs because of their smaller frame and build (Stevenson et al., 2015; Cloutier et al., 2021). Multiple studies have found that a large proportion of child pedestrian MVCs occurs within school travel hours and in close proximity to schools (LaScala et al., 2004; Warsh et al., 2009). Additionally, there has been a movement toward using active transportation modes for school travel as a way to increase the physical activity of children (Sallis et al., 2006; Faulkner et al., 2009; Larsen et al., 2009; Buttazzoni et al., 2019). While this may be beneficial for the cardiovascular fitness and health of children, it also exposes children to vehicular traffic (Cloutier et al., 2021; Clark et al., 2016; Larsen et al., 2012). The promotion of active transportation, the vulnerability of children to MVCs and increased rates of child pedestrian MVCs around schools indicate a need to identify hazardous areas and implement road safety interventions.

Common interventions targeting student safety are education programs and the implementation of crossing guards at busy intersections. While education programs have been shown to change student pedestrian behaviors (Duperrex et al., 2002; Schwebel et al., 2014), there is no evidence that education programs decrease rates of pedestrian MVCs (Cloutier et al., 2021). Additionally, this places much of the burden and blame for student safety on students and schools, disproportionately (Cloutier et al., 2021). Traffic calming measures have been found to be effective in reducing pedestrian MVCs and creating a safer, more walkable environment (Rothman et al., 2014). However, these built environment interventions pose a significant investment for municipalities who often opt for a more cost-effective approach like crossing guard implementation. While crossing guards are generally accepted to have a positive influence on student safety (Schwebel et al., 2012), existing studies have found conflicting evidence. A quasi-experimental study (Rothman et al., 2015) found that the implementation of new crossing guards had no significant impact on rates of pedestrian MVCs while an observational study (Rothman et al., 2017a) found an association with higher MVC incidence.

There has largely been a lack of accurate and reliable pedestrian volume data used in MVC studies, especially at the level of individual intersections and street segments (Cloutier et al., 2021; Fridman et al., 2021). This makes estimating current pedestrian MVC exposure risk difficult as many studies use area-wide pedestrian volume proxy measures (population density) which may not accurately represent actual pedestrian volumes and flows (Wier et al., 2009; Cottrill & Thakuriah, 2010; Warsh et al., 2009). This may be further exacerbated when focusing on child and adolescent pedestrian volumes, which are more likely to be clustered in and around schools and at specific times of the day. Using street level student pedestrian volumes will allow for more detailed analysis and identification of hazardous areas for children during school commutes.

3.1.1 Research Objective

The objective of this research is to identify which areas in London, Ontario pose the highest MVC risk to student pedestrians during their school commutes. To address this objective, the pedestrian volume of primary and secondary school students will be estimated for all road segments in the City of London during their school commutes. The student pedestrian volumes will be overlaid with a measure of MVC risk derived from the previous chapter, creating a risk score and revealing the areas that pose the highest risk to the largest number of students. Current crossing guard locations will also be analyzed against these high-risk locations to assess the current suitability of student safety measures implemented by the City of London. It is expected that the findings of this study will be valuable for informing policy regarding student safety interventions, particularly for the location of crossing guards.

3.2 Methods

3.2.1 Data

Data on school locations and student home postal codes from 2019 were obtained for 108 schools in London, Ontario from Southwestern Ontario Student Transportation Services through an agreement with the Human Environments Analysis Laboratory at Western University. The data include the school the student attended, bus eligibility, the postal code of that student and their grade level. From this dataset, we selected students who attended school within London, lived within 1.6km of their school, were not eligible for bus service and assumed to be walking school (n = 31,258 students). Some postal codes were outside of the City of London and these students were excluded (<0.3% of the data met this criteria). The centroids of postal codes (n = 13,328) in London were sourced from DMTI Spatial. School building location and property boundary data were sourced from the Ontario Ministry of Education. The location of crossing guards was accessed through the City of London's Open Data site (https://opendata.london.ca/) and cross-referenced with updated crossing guard location data from the City; there were 12 crossing guards located at mid-block road segments while 95 crossing guards were located at intersections (Figure 3-1).

Closest facility analysis requires the creation of a network dataset that represents the pathways available for travel (i.e. a road network). To model student pedestrian travel, we generated a circulation network comprising the road network, as well as all trails, walkways and multi-use paths. These datasets were available through the City of London's Open Data site. These individual networks were combined to create a circulation network, a network that also includes shortcuts or cut-throughs that more accurately represents pedestrian accessibility (Figure 3-1). The consideration of shortcuts in pedestrian network analysis is important because it can increase the connectivity of a network and decrease travel distances due to the use of informal paths (Giles-Corti et al., 2011; Clark et al., 2016; Larsen et al., 2012). We further cleaned and improved the pedestrian circulation network derived from the municipal data source in three ways, as demonstrated in Figure 3-2:

1. Duplicate linear features were found and removed.
2. Using GIS software, we digitized additional links/paths/cut-throughs using satellite imagery as a reference.
3. Using GIS software, we digitized entrances to each schools' boundary polygon as identified through satellite imagery overlaid with the circulation network and boundary polygons.

We digitized a total of n = 413 entrances for the n = 108 schools in London, Ontario. The entrances identified in step 3 above were used as the destination locations for the subsequent closest facility analysis. All spatial manipulation and analyses were conducted in ArcGIS Pro.

Figure 3-1: The distribution of crossing guards (n = 107) and schools (n = 108) displayed on the circulation network, within the city limits of London, Ontario.

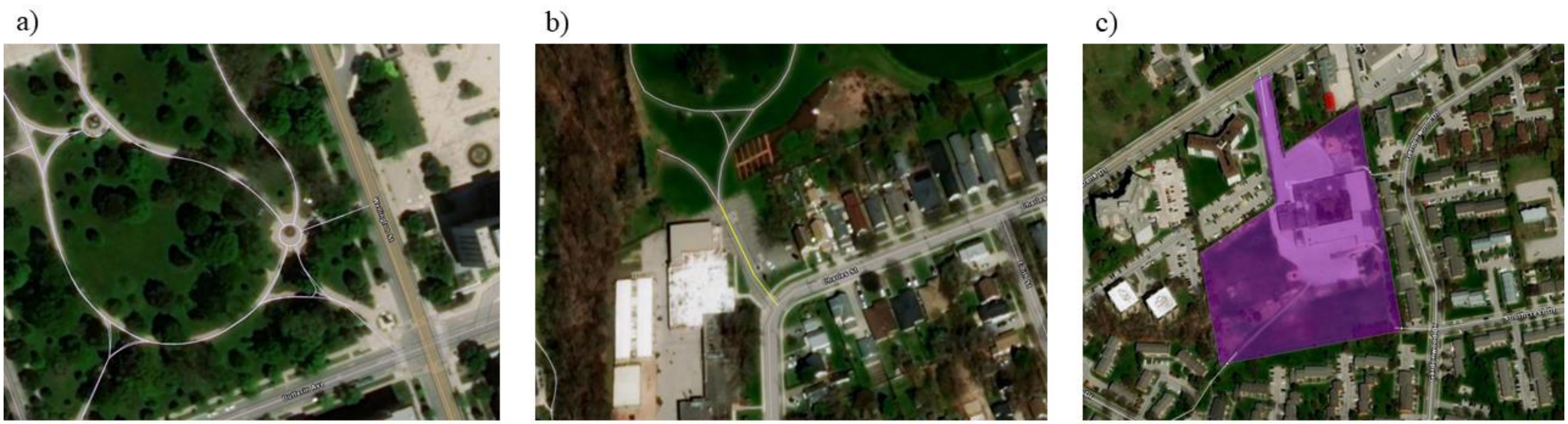

Figure 3-2: a) An example of duplicate linear features that were removed. b) An additional link (shown as yellow line) that was digitized. c) Digitizing the entrances (shown as green points) to a school's boundary (shown as purple polygon).

3.2.1.1 MVC Risk Measure

The measurement of MVC risk is derived using the outputs of the analyses in Chapter 2. The mean density value will be used as the measure of MVC risk for student pedestrians in London (Figure 3-3). The mean density values were calculated using MVC data from 2010 to 2019, a network-based KDE method, normalized using traffic volume and averaged by year (see Chapter 2 for more details). The higher the density value, the more collisions occurred at that location or in close proximity to that location. The mean density value from 2010 to 2019 was used to determine which areas were consistently at risk of MVCs. While the density values are based on all collision types (automobile-automobile, automobile-cyclist, automobile-pedestrian), we use it here as a proxy representative of the overall MVC risk level of a mid-block road segment or intersection.

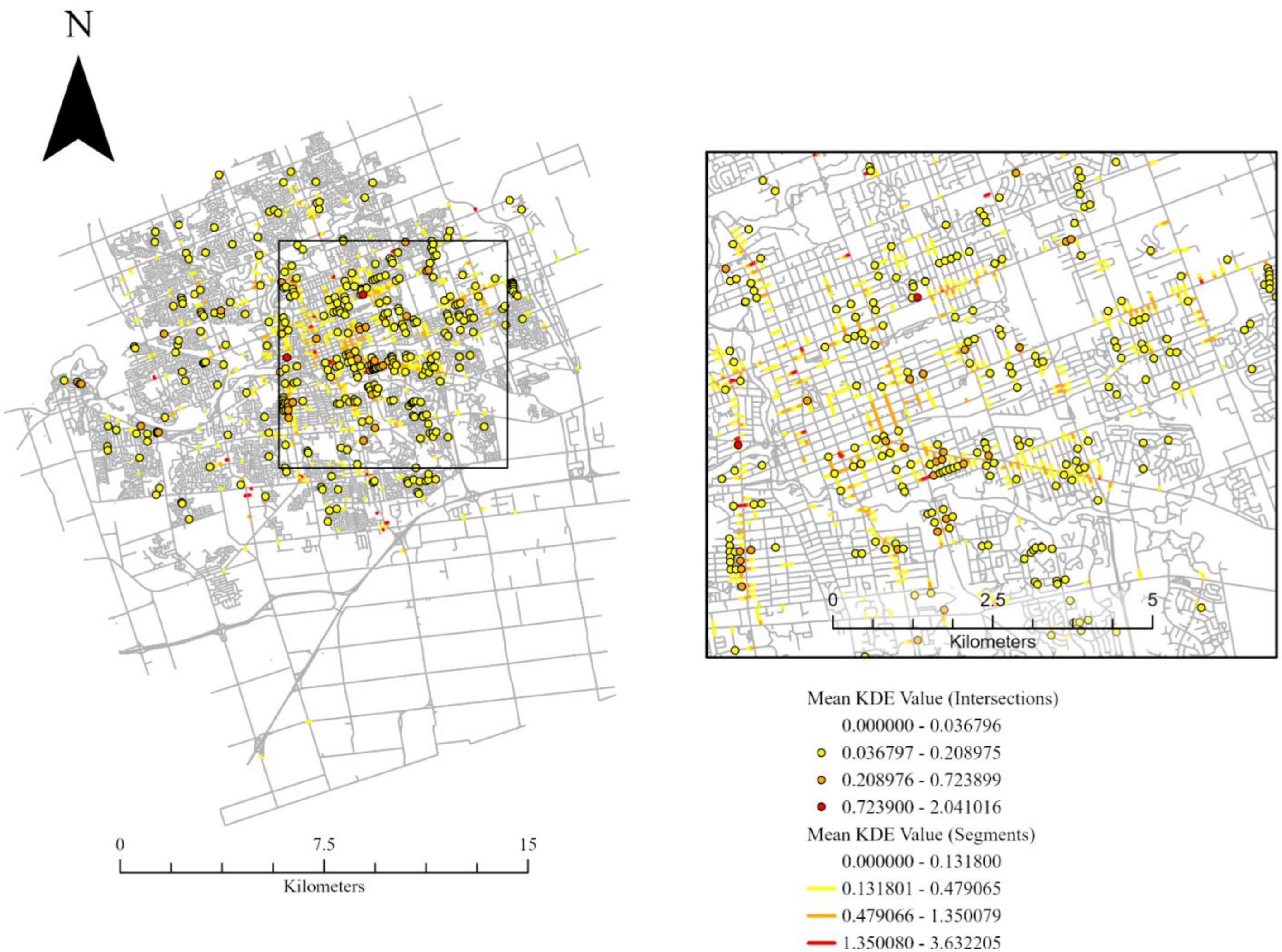

Figure 3-3: Mean KDE value for intersections and mid-block segments across London, Ontario.

3.2.2 Data Analysis

3.2.2.1 Closest Facility Analysis

To generate a student pedestrian volume, a closest facility analysis method was employed. This analysis was conducted using ESRI's Network Analyst Toolbox within ArcGIS Pro. Several studies have used a shortest network path analysis to determine the most likely routes for pedestrians and subsequent exposure estimation (e.g., Li et al., 2020), and in particular child pedestrians commuting to school (Schlossberg et al., 2006; Larsen et al., 2012; Bennet & Yiannikoulias, 2015). Previous research has often chosen to use the main school entrance as the destination for students to reach; however, school grounds often have multiple entrances that students use to access the school property and/or building. To account for this variability, instead of determining the shortest network path between a student's home and the main entrance of the school, we use the shortest network path to the nearest school entrance (Giles-Corti et al., 2011) where school entrances were defined manually by digitizing where the circulation network connected to school property boundaries.

The closest facility analysis was run for each school with student data available (n = 108 schools) where the postal code centroids of students attending that school were used as the origin locations (incidents) and each school's entrances were used as destination locations (facilities). For each student, the nearest school entrance was found and the shortest network path along the circulation network was calculated. The public school board policy in this study area dictates that students that live greater than 1.6km from their school are provided bus service, therefore we further excluded students that had a shortest network distance > 1.6km network distance to their nearest school entrance as they were eligible for bus services (5,065 students were removed from this analysis based on this criteria). Several previous studies have used bus eligibility as exclusion criteria in estimating which children are walking to school and the routes that they take (Schlossberg et al., 2006; Larsen et al., 2012; Clark et al. 2016). After the closest facility analysis was conducted for each of the n = 26,103 students who lived within 1.6km of a school entrance, the paths for all students were summed along each road segment and intersection to create a student pedestrian volume map for London, Ontario.

3.2.2.2 Risk Exposure Analysis

Our analysis looks to identify the areas that pose the greatest risk to student pedestrians based on a combination of calculated MVC density values and student pedestrian volumes. To do so, we created a risk score that represents the risk of MVC occurrence involving a student pedestrian. This was calculated by multiplying the mean KDE value of a location by that location's student pedestrian volume. The risk score for all intersections and mid-block locations in London, Ontario was mapped.

To identify the riskiest areas for student pedestrians, the mid-block segments and intersections with a student pedestrian volume of 40 students or greater were selected. These mid-block segments and intersections were then ranked according to their risk scores and the top 15% of each road type were selected. The threshold values of 40 students and 85th percentile of exposure risk were used by the Ontario Traffic Council in their guide for the assessment of areas in need of crossing guard supervision (2017). These areas were deemed the highest risk for student pedestrians in London, Ontario.

3.2.2.3 Crossing Guard Location Assessment

Crossing guard locations were compared with the areas identified as posing the greatest risk to student pedestrians. While crossing guards should have a positive effect on child pedestrian safety, studies have found conflicting evidence. A quasi-experimental study by Rothman et al. (2015) found no significant change in MVC rates after the implementation of new crossing guards, while an observational study by Rothman et al. (2017a) found that crossing guards were associated with higher MVC rates. Crossing guards are often situated at areas with a higher volume of student pedestrians, however it can be argued that they should be located at areas with high MVC risk and relatively high student pedestrian volumes (Ontario Traffic Council, 2017). Assessing where crossing guards are currently located in relation to risky areas can lead to the identification of gaps in the crossing guard network. This was done by overlaying crossing guard locations with the mid-block segments and intersections found to pose the highest risk to student pedestrians in London, Ontario.

3.3 Results

3.3.1 Student Pedestrian Volume

The shortest network path from postal code centroid to closest school entrance was calculated for n = 26,103 students and merged to create a student pedestrian volume map (Figure 4). The maximum pedestrian volume along a mid-block segment was 495 students and the mean volume of mid-block segments with at least one student pedestrian was 21 students. At intersections, the maximum and mean student pedestrian volumes were 383 and 32 students respectively.

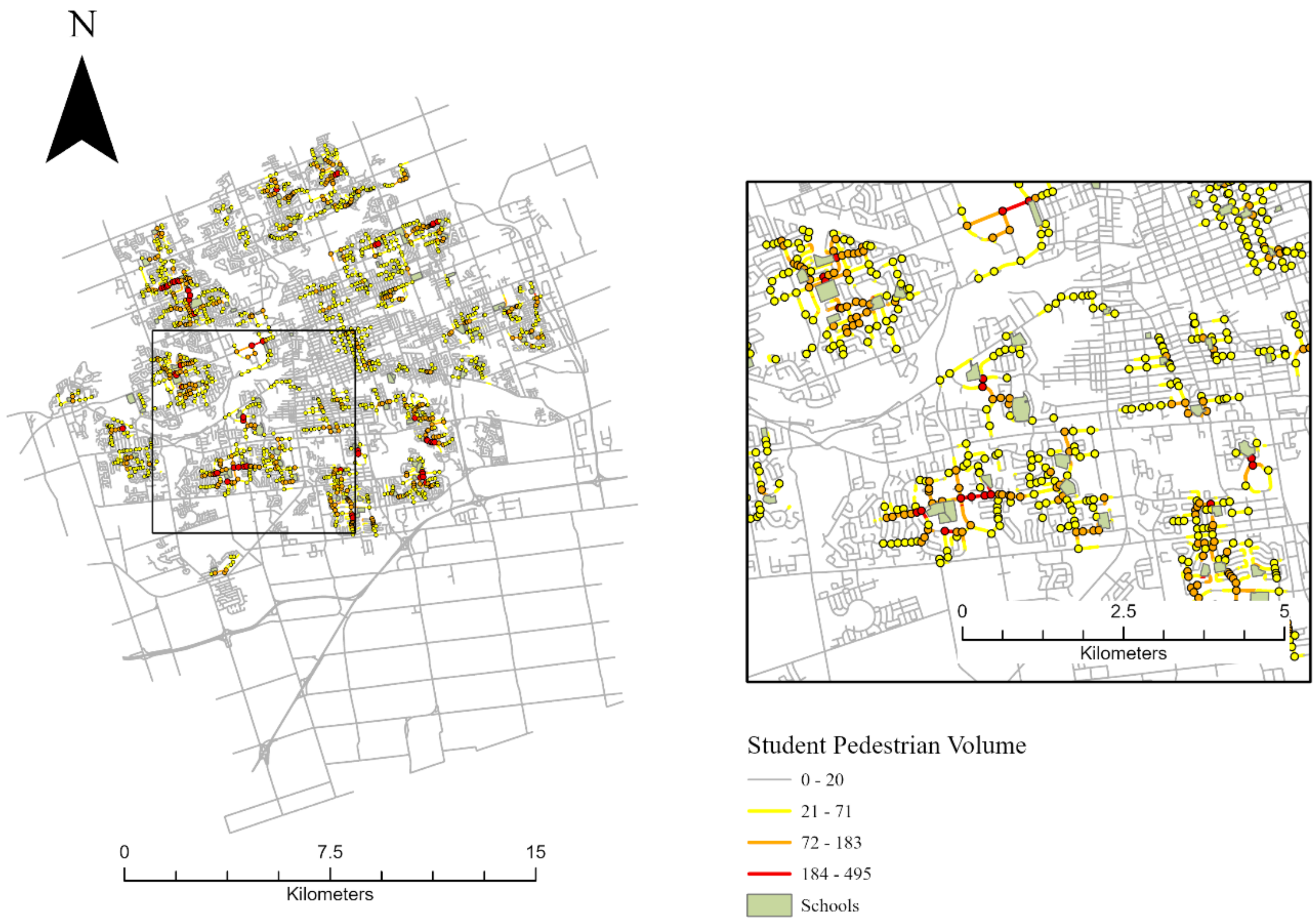

Figure 3-4: Student pedestrian volume in London, Ontario based on n = 26,103 students attending n = 108 schools.

3.3.2 Pedestrian Risk Exposure

There were n = 12,497 mid-block segments and n = 2,096 intersections with a risk score greater than 0. The mean risk score at these intersections was 0.42 with a maximum of 28.5 while the mean risk score at the mid-block segments was 0.98 with a maximum of 510.4. Many of these segments and intersections have very small risk scores as evidenced by very low median values (Table 1). The risk scores are visualized in Figure 5.

Table 3-1: Summary statistics for risk score by road type.

Road Type	Mean	Median	Maximum	Standard Deviation
Mid-Block Segments (n = 12,497)	0.98	0.09	510.4	7.1
Intersections (n = 2,096)	0.42	0.06	28.5	1.4

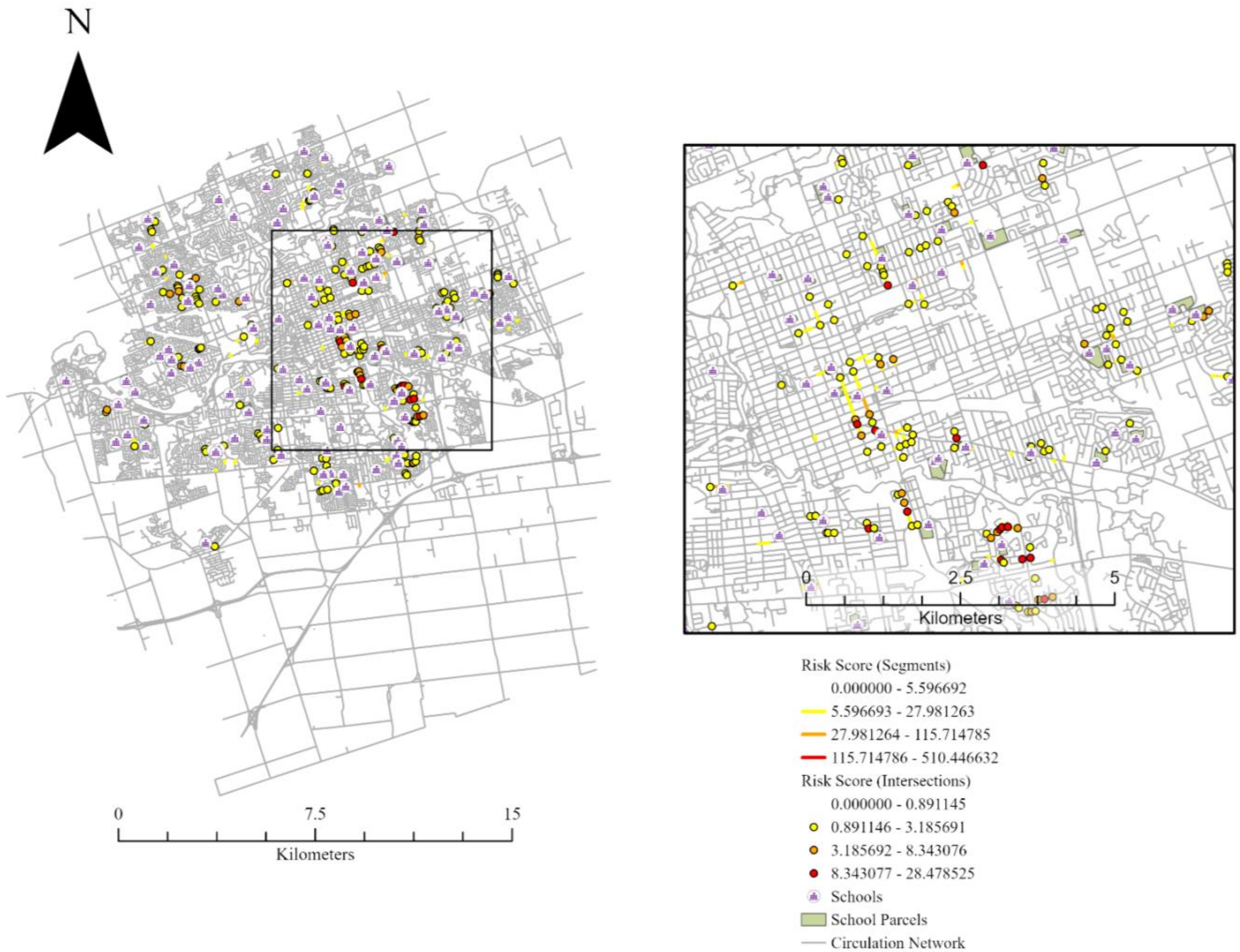

Figure 3-5: Risk score for mid-block segments and intersections displayed alongside schools in London, Ontario.

3.3.3 High Risk Analysis

Selecting the mid-block segments and intersections with at least 40 student pedestrians resulted in the removal of n = 60,508 (95%) segments and n = 4,505 (85%) intersections. Of these segments and intersections, the top 15% according to risk score were selected, resulting in n = 521 segments and n = 120 intersections (Figure 3-7). The riskiest mid-block segments had an average risk score of 10.6 (Max: 510.4) while the riskiest intersections had an average risk score of 3.36 (Max: 17.3). While it seems that intersections have much lower risk scores overall, they have the higher average student pedestrian volumes (Table 3-2).

Table 3-2: Student pedestrian volume summary statistics for the riskiest mid-block road segments and intersections.

Road Type	Mean	Median	Maximum	Standard Deviation
Mid-Block Segments (n = 521)	94	67	495	65
Intersections (n = 120)	125	93	380	86

3.3.4 Crossing Guard Location Assessment

Crossing guards (n = 107) were located at areas with relatively high student pedestrian volumes (mean = 83, max = 383). However, crossing guards are thought to be typically deployed at areas with the highest student pedestrian volumes. Which is not the case in London, for the 50 intersections with the very highest volumes only 8 had crossing guards posted.

When crossing guard locations were overlaid with the 521 mid-block segments and 120 intersections determined to be high risk, only nine (8.4%) crossing guards were located at a high risk area. That is, very few of the 107 crossing guard locations corresponded to intersections or road segments with the highest MVC risk. Only 19 crossing guards were located less than 50m from a high risk area, a radius deemed appropriate for crossing guard effectiveness (Rothman et al., 2015). This is further visualized in a scatter plot in

Figure 3-6. The red dots are areas that have crossing guard supervision, the intersection plot has more crossing guards as that is where they are usually implemented. The points are plotted according to their mean KDE values and student pedestrian volume, the highest risk areas are towards the upper right-hand corner, while the lowest risk areas area towards the bottom left. Ideally, the red dots should be at the upper right area of the plot, however they seem to be dispersed evenly throughout.

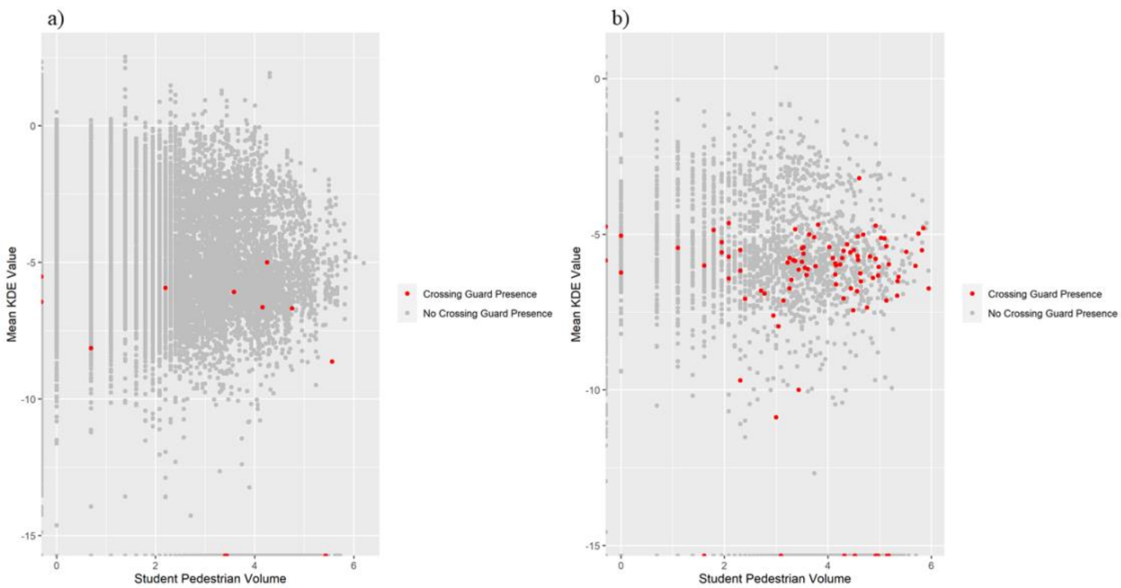

Figure 3-6: a) 12 mid-block segments and b) 95 intersections with crossing guard presence displayed with unsupervised segments and intersections according to mean KDE value and student pedestrian volume.

Figure 3-7: The riskiest mid-block segments and intersections in London, Ontario overlaid with crossing guards and schools.

3.4 Discussion

3.4.1 Student Pedestrian Volume and Exposure

The focus on student pedestrians in our study allows for a more accurate calculation of pedestrian volume due to the availability of origin (home) and destination (school) data. However, it is significantly limited in scope as this study only looks at student pedestrians during their commute to school. Child pedestrian behaviors and routing outside of school commute times and overall pedestrian pathing were outside of the scope of this study. Outside of school commutes, children tend to be restricted to areas around their neighborhood, particularly parks and other recreation areas, as they typically rely on their parents to drive them to further locations (Rothman et al., 2014; Stevenson et al., 1996; Braddock et al., 1994). These walking behaviors are more difficult to predict and estimate to create a child pedestrian volume.

The areas in London with the highest student pedestrian volumes are mostly around school entrances, which is expected. While unsurprising, these areas still pose a great risk to student pedestrians commuting to school as there still is a large potential for conflict with vehicles when parents are picking up/dropping off their children (Rothman et al., 2017b). Higher vehicle volumes and higher student pedestrian volumes during school commuting times are periods of exceptionally high student pedestrian exposure to MVCs. The risk of these segments or intersections is even greater if the school is located on a major road or intersection, further exposing students to higher volumes of vehicular traffic. There is conflicting evidence in pedestrian MVC literature concerning the relationship between pedestrian exposure and pedestrian safety. Studies have found that more pedestrians walking have been shown to have an inverse relationship with MVC occurrence (Elvik & Bjornskau, 2017; Jacobsen, 2015), while studies have also found that areas with more children commuting to school are associated with higher rates of pedestrian injury (Rao et al., 1997; Gropp et al., 2013). It has been suggested that drivers may exercise more caution when in close proximity to higher volumes of pedestrians, however this may be negated by the urgency drivers might feel during rush hour commutes which often correspond with school start times. Additionally, previous studies likely used area wide approximations of pedestrian volume, which makes it impossible to distinguish possible street level differences which are masked by the area wide relationship. For example, road segments with high pedestrian volumes in downtown areas may have lower MVC occurrence due to lower vehicle speeds while road segments with high pedestrian volumes near a school may have higher MVC occurrence due to potentially higher vehicle speeds or more opportunities for conflicts between road users.

The lack of accurate and reliable pedestrian volume has been an issue in MVC literature (Cloutier et al., 2021; Fridman et al., 2021). Without pedestrian volumes, accurate exposure estimation cannot be calculated. Existing pedestrian MVC literature has used area wide measures such as population density or proportion of zoning types by census tract as proxies for pedestrian exposure/activity (Wier et al., 2009; Cottrill & Thakuriah, 2010). The use of area wide approximations of pedestrian volume can lead to inaccuracies and a lack of granularity when identifying areas with high pedestrian MVC risk (Cloutier et al., 2021). More precise methods for calculating pedestrian volume involve manual counts of pedestrians (Rothman et al., 2014), the use of Google Street View and a big data approach (Yin et al., 2015) and pedestrian counting technologies (Kothuri et al., 2017). Manual counts are only able to provide a brief snapshot of pedestrian volume at locations where counters are present, resulting in a significant temporal and spatial gap. The use of Google Street View and a big data approach is promising, but the use of a static snapshot of a street for pedestrian detection is heavily reliant on when the image was taken; the availability of more data will aid in the accuracy and reliability of this method. Counting technologies like inductive loops or thermal cameras were found to be unreliable for pedestrian counts and while passive infrared counters were accurate at intersections, like manual counts, they are limited spatially. While pedestrian signal actuation has been found to have potential as a cost-effective method for approximating pedestrian demand at intersections, they are limited to signalized intersections and are unable to provide exact volume counts.

3.4.2 Measure of MVC Risk

While the MVC risk was based on density values calculated using fatal or serious injuries resulting from all collision types, not pedestrian MVCs specifically, these collisions are the most hazardous and are indicative of a potentially unsafe area for all road users. Density values were used instead of absolute MVC counts to account for the spread of risk that results from an MVC occurrence (Xie & Yan, 2008). The density values were calculated for each year from 2010 to 2019 and averaged to determine the consistency of MVC risk at a location.

3.4.3 High Risk Areas

Ideally, no student should be exposed to areas with high MVC risk. However, a minimization of student pedestrian exposure to high MVC risk is more realistic goal. Overall, the risk scores of mid-block segments and intersection in London are relatively low with a mean of 0.98 and 0.42 respectively. While this may seem like a positive sign for student pedestrian safety in London, there are still several areas that have substantial risk scores and may warrant attention. We identified 521 segments and 120 intersections as high risk areas for students in London, these areas had average risk scores of 10.6 and 3.36 respectively. This, in addition to average student volumes of 94 students at high risk mid-block segments and 125 students at high risk intersections indicate that there are a significant number of students exposed to areas with high MVC risk. These areas pose the most danger to most student pedestrians and should be addressed to ensure a safe walking environment for students.

A previous study by Warsh et al. (2009) examined the MVC risk for students within school zones, finding that areas closest to a school had the highest risk for MVCs. The study also found that pedestrian MVCs also were more likely to occur during school commute times, further highlighting the need to address the dangers surrounding student safety during school travel. However, this study lacks the pedestrian exposure data that limits many studies in existing literature. In this study we were able to more accurately estimate pedestrian volumes and flows, allowing for a more detailed assessment along road segments and at intersections of student pedestrian exposure to MVC risk.

3.4.4 Crossing Guard Location

We found that of the 107 crossing guards currently deployed in London, nine (8.4%) were located directly on a high risk area. Considering there are 521 mid-block road segments and 120 intersections found to be high risk areas for students, this was a surprising and concerning outcome as it suggests that there are hazardous areas, with high MVC risk, that are not supervised and may pose significant danger to student pedestrians. It can be argued that crossing guards have a greater effect radius than one exact location, with Rothman et al. (2015) using a 50m buffer around crossing guards. Using this criterion, it was found that 19 (17.8%) crossing guards were located near (within 50m) of a high risk area. The small proportion of crossing guards positioned near a high risk area indicates that the placement of crossing guards in London may need to be reassessed. The Ontario Traffic Council recommends that crossing guards be placed at locations with more than 40 student pedestrians and rank above the 85th percentile in terms of exposure risk. While the measure of exposure risk in this study differs slightly from the measure used by the Ontario Traffic Council, our assessment has found that over 80% of crossing guards in London may need to be relocated or re-evaluated. The Ontario Traffic Council only considered traffic volume and pedestrian volume for its exposure measure while we used MVC risk in addition to pedestrian volume.

The discordance between crossing guard location and high risk areas could be explained by the established use of pedestrian volume and traffic volume as the rationale for crossing guard placement. Typically, crossing guards are placed in areas with the highest student pedestrian volumes without the consideration of MVC risk (Ontario Traffic Council, 2017). Assessing crossing guard location in London using this criterion still indicated poor placement. The average student pedestrian volume at each crossing guard location was 83; while relatively high, there are many areas with higher student pedestrian volumes without crossing guard supervision. Of the 50 intersections with the highest student pedestrian volumes, only eight were supervised by a crossing guard. This is concerning as this indicates there are many intersections where large volumes of students are crossing with no crossing guard presence. The lack of supervision makes students more vulnerable to MVCs due to their relative inexperience in navigating traffic situations and potential conflicts, particularly for younger students (Cloutier et al., 2021; Bennet & Yiannakoulias, 2015). Interestingly, we found that there were four crossing guards that had a student pedestrian volume of zero. This is most likely a function of using shortest path distance as the only factor in route choice. In reality, these crossing guards almost certainly do not have zero students to supervise, as students (and parents) likely consider the location of crossing guards when choosing where they cross a street. Overall, crossing guards in London are being placed in areas with relatively high student pedestrian volumes, however they are missing at a vast majority of the busiest intersections which suggest a lack of location suitability.

School assignment data for crossing guards was unavailable and it is not clear whether they are in fact assigned to a school, so the distance to the nearest school was calculated. The average distance from a school was 174.7m which was farther than expected, however one crossing guard was 790.2m from the nearest school which likely skewed the mean. This outlier could be explained by the fact that not all data for all schools in London were available (n = 18 schools were excluded), it is possible that this crossing guard was located proximal to a school not included in this study. Taking this and a median distance of 110.8m into consideration, the average distance to a school is relatively short. This is appropriate as the areas adjacent to a school typically have the highest student pedestrian volumes and are the most hazardous for students (Warsh et al., 2009; Ontario Traffic Council; 2017). However, crossing guards may not currently be placed in the optimal areas close to a school as evidenced by the previous finding of the lack of supervision at the busiest areas.

Large and busy intersections may pose a challenge to students attempting to cross due to their relative lack of experience (Cloutier et al., 2021; Bennet & Yiannakoulias, 2015). The ability to adhere to traffic signals and conventional street crossing procedure while being aware of all other road users in the environment is difficult for adults, much less inexperienced children. This difficulty is further exacerbated at larger intersections (Rothman et al., 2010). Not only do students have to cross a longer distance, but there are also more road users to be aware of and assess. Therefore, it would be appropriate for crossing guards to be placed at these difficult to navigate locations. We found that 46

(43%) crossing guards were located on streets or intersections classified as *arterial* streets. According to London's official plan, arterial streets are designed for high traffic volumes traveling at speeds of 50-80 km/h and have at least two lanes (City of London, 2018). In terms of assisting students in crossing the largest intersections, the suitability of crossing guard location seems to be adequate as not all schools are proximal to arterial streets.

3.4.5 Student Pedestrian Safety in London

The promotion of active travel by public health officials necessitates the need to create a safe walking and cycling environment. Increasing rates of obesity and sedentary lifestyles among children in developed nations has led to a focus on active travel promotion for students commuting to school (Lubans et al., 2011). The existing vulnerability of children, child pedestrians in particular, to MVCs and injuries sustained as a result of an MVC is well documented in road safety literature (Schwebel et al., 2012; Connelly et al., 1998). It is difficult to assess the current situation with child pedestrian MVCs in London due to the lack of data. However, the adoption of Vision Zero principles and our findings of a large number of high risk areas in London indicate a need for intervention. While it can be argued that a city's budget should not be used on interventions when there is no hard evidence that children have been involved in MVCs, preventative measures should be taken in issues involving public health, especially children's health. If the City of London truly subscribes to the Vision Zero principle that no serious injury or fatality should result from an MVC, retroactive measures should be recognized as insufficient and a more proactive approach should be adopted.

The adoption of Vision Zero in 2017 and the creation of the Complete Streets Design Manual in 2018 are positive steps for London's road safety commitment. However, there is no clear plan for any kind of implementation of the road safety improvements like protected intersections, bike lanes or transit islands that have been briefly outlined on the City's road safety site (https://london.ca/roadsafety). This is in stark contrast to the multiple detailed reports on the high level of road construction and renewal projects available on the City's road construction site (https://london.ca/roadconstruction) with vague information on improvements to active transportation infrastructure. Education programs play an important part role in road safety, however in the context of student safety, they are typically targeted at students rather than drivers. Additionally, for programs like Active & Safe Routes to School (ASRTS) (http://www.activesaferoutes.ca/), the onus for adoption falls to the school themselves. Only 30 schools in London are currently listed as participants in the ASRTS program. This shifts much of the burden for student safety, disproportionately, to students and schools. Interventions for school safety by municipalities usually take the form of crossing guard implementation, with built environment interventions often cited as too expensive. However, in the case of London, many of the crossing guards seem to be located at less than ideal areas and the number of crossing guards may be insufficient for the number of schools and students. According to recommendations by the Ontario Traffic Council, traffic volume and pedestrian volume are the main criteria when warranting the placement of a crossing guard (2017). It was found that using these criteria, there were many areas with large volumes of students crossing unsupervised. Further, assessing crossing guard location considering MVC risk yielded more concerning results as the areas posing the highest MVC risk to the most students had little crossing guard presence.

Due to resource limitations, it is critical to identify the most appropriate locations for crossing guards. Based on our findings, we recommend that existing crossing guards be relocated to areas with the greatest risk scores, which are the areas with the highest student pedestrian volumes as well as the highest MVC risk. It is likely the current number of crossing guards are insufficient to cover these areas, and despite the conflicting evidence surrounding crossing guards, more crossing guards should be hired to ensure a comprehensive coverage of high risk or high volume areas. In recent years, nine crossing guard locations have been cut citing a standard for crossing guard placement as the rationale for the removals (CTV London, 2014). While two crossing guard locations were added there was still a net loss in crossing guards, which suggests there was little attempt to identify more suitable areas for crossing guards. Finally, we recommend not only that more active transportation facilities be constructed, but the walkability and cyclability of these areas be prioritized. That is, paint on road surfaces and rudimentary sidewalks are insufficient and potentially hazardous, encouraging active transportation when it is not safe for users. High quality, protected bike lanes in addition to sidewalks with sufficient built environment barriers like street trees or planters are needed to effectively ensure road safety for all users. While the lack of budget will likely be cited, there is evidence of numerous road construction and road expansion projects that are taking place in London (https://london.ca/roadconstruction). This shows a clear prioritization of drivers and vehicles rather than active transportation road users, which is in contrast to Vision Zero principles.

3.4.6 Limitations

From 2010 to 2019, there were a total of 1,656 MVCs (2.14% of all MVCs) involving pedestrians in London, 96% of which resulted in a serious injury or fatality. However, it is not possible using our data source (collected by the London Police Service) to distinguish which collisions involved children as only the age of the drivers involved was available. The lack of pedestrian MVC data, much less child pedestrian data limited our study in the ability to assess the actual MVC risk posed to child pedestrians. However, using mean density values calculated using the most dangerous collisions provides a sufficient proxy measure for MVC risk.

Student data for n = 108 schools in London were included in this study, according to the City of London Open Data site there are a total of n = 126 elementary plus secondary schools. The data for 18 schools were unavailable, these include several private schools, provincial schools, special education schools and four French first language public schools. This means the student pedestrian volume and flows that were estimated in this study may not be wholly representative of London's student pedestrian volume; however, it is likely sufficient for representing the overall spatial pattern of student pedestrian volumes and flows. Additionally, these missing specialized schools typically have a larger catchment area and have students attending from across the city. It is reasonable to assume that a small number of students would be walking to these schools and would not affect the spatial pattern and volume of student pedestrian flows that was calculated.

3.4.7 Future Considerations

Previous studies have contested the use of shortest travel distance in pedestrian route prediction (Sevtsuk & Kalvo, 2022; Lam et al., 2014), with route discordance also found for children walking to school (Buliung et al., 2013). However, a study by Guo and Loo (2013) found that pedestrians in New York City consider travel distance as the primary factor in route choice and Cooper et al. (2010) found that children tend to follow the most direct routes between home and school. While the spatial pattern of student pedestrian flows would likely be quite similar, future use of other factors like elevation change or signalized crossings in route choice estimation could lead to a more accurate representation of actual student pedestrian paths.

The availability of accurate and detailed pedestrian volume data has been a well-documented issue in pedestrian MVC analysis. While we were able to more accurately estimate pedestrian volume than previous studies, our sample was limited to students. Additionally, the use of postal code centroids has been found to have distance discrepancies of 68-82m when determining accessibility to schools in London (Healy & Gilliland, 2012); however, it should not greatly influence the spatial pattern of student pedestrian flows and also provides a modicum of anonymity versus using exact student home address data. The identification of shortest network paths for each student leads to privacy concerns which is mitigated by the aggregation of these paths. However, the scalability of this method for wider pedestrian volume estimation is difficult as pedestrian paths usually involve multiple stops and may be interspersed with other modes of travel. The consideration of data privacy and tracking is another issue entirely and will likely pose the greatest challenge for the applicability of this method for general pedestrian volume estimation.

While our study was able to estimate student pedestrian volume and exposure at street level, future research should increase the level of granularity. The ability to accurately identify which side of the street a pedestrian was walking or where they chose to cross the street would allow for more targeted interventions or analysis.

3.5 Conclusion

The findings of this study suggest the inadequacy and unsuitability of current student pedestrian safety measures during school commutes in London, Ontario. We have identified several high risk areas, areas with high MVC risk and a large volume of student pedestrians that are currently unsupervised by crossing guards. Additionally, the placement of crossing guards is largely incongruent with the areas with the highest student pedestrian volumes, further emphasizing a need to evaluate and reconfigure crossing guard location in London. The promotion of active travel to school and the inherent vulnerability of children to MVCs necessitates the creation of a safe and walkable environment. This goes beyond the implementation of crossing guards and should include the promotion of educational programs like ASRTS and built environment improvements that protect active transportation users like protected bike lanes and the addition of street side buffers. A clear action plan on how substantial, high quality road safety improvements are going to be made, supported by significant investment in these built environment interventions, is required should the City seek to uphold its Vision Zero principles.

3.6 References

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Chapter 4

4 Conclusion

4.1 Chapter 2 Findings

In Chapter 2, MVC hotspots in London were identified and their temporal trends from 2010-2019 were measured to assess the prevalence of MVCs across space and over time. Additionally, the influence of the street network's built environment characteristics on the identified MVC hotspots were measured. Using the 12,283 MVCs that occurred in London from 2010-2019 that resulted in a fatality or serious injury, a network-based KDE method was employed in conjunction with a hotspot categorization method. This resulted in the identification of 2,328 mid-block hotspots and 308 intersection hotspots. The analysis of built environment influences on these MVC hotspots produced several key findings. It was found that bike lanes have a statistically significant reductive effect on MVC hotspots at both mid-block and intersection locations, particularly in emerging hotspots. Alternatively hedges and sidewalks were found to have a statistically significant positive association with MVC hotspot presence at mid-block segments and intersections, while on-street parking was found to be significantly associated with an increase in MVC hotspots at mid-block locations. The results of the study reported in Chapter 2 have implications for road safety policy in London and its Vision Zero goals. The reductive influence of bike lanes on MVC hotspots is an encouraging revelation given London's recent investment in cycling infrastructure across the city. The construction of high-quality separated bike lanes should be prioritized given its protective qualities for both cyclists and pedestrians, the most vulnerable road users. A more concerning finding, however, is the statistically significant positive association that sidewalks have with MVCs in London. The promotion of walking and active travel requires a safe environment for pedestrians to use. The positive association that sidewalks have with MVC hotspots indicate that the current pedestrian environment in London may not be safe or walkable. MVCs resulting in fatalities or serious injuries often are a result of high traffic speeds, which when located on streets with sidewalks and little to no street side buffer, pose a significant hazard to pedestrians. Additionally, most collisions involving pedestrians are likely to result in a fatality or serious injury. This suggests that current sidewalk infrastructure may be inadequate regarding pedestrian safety and further investment into traffic calming or exposure reduction measures should be considered, such as increasing the distance between sidewalk and road via street side buffers such as grassy medians or bike lanes. Built environment features like hedges and on-street parking have been shown to have a statistically significant additive effect on MVC hotspots, with sightline obstruction likely playing a large role. While these features may decrease visibility, they also have traffic calming qualities. This means that the implementation of these features should be more calculated and deliberate. Overall, the road design of London’s street network should encompass the needs of all road users and emphasize the construction of built environment features that make the overall road environment safer.

4.2 Chapter 3 Findings

The exposure of school-age children in London to high MVC risk areas and the suitability of current crossing guard locations were assessed in Chapter 3. Using student home postal code data and school entrances, shortest network paths for each student (n = 26,103) in the study were calculated. This was then aggregated to create a student pedestrian volume, allowing for an estimate of exposure to MVC risk for students in London, Ontario. Overlaying mean density values measured in Chapter 2 onto the student pedestrian volume, several high risk areas were identified. These areas were found to pose the greatest risk to the most student pedestrians commuting to school. These areas were overlaid with crossing guard locations, resulting in little overlap. Additionally, assessment based solely on student pedestrian volume also indicates a potential unsuitability of current crossing guard placement. With the recent promotion of active travel for school commutes and the vulnerability of children to MVCs, there may be a need to reassess current school safety protocols and measures in London, beyond crossing guard placement. Programs like ASRTS should be promoted and built environment interventions like street side buffers or traffic islands should be implemented to ensure pedestrian safety should the City endorse Vision Zero ideals.

4.3 Limitations and Future Considerations

A major limitation of this study is the use of MVC data obtained from police records. The data reliability and under-reporting issues of police data has been well documented in MVC literature (Amoros et al., 2006; Janstrup et al., 2016; Watson et al., 2015). While future work in the field would only benefit from an increase in quality and quantity of MVC data, current data derived from police records still hold value for MVCs involving injuries or fatalities as unreported MVCs typically result in property damage only. The use of MVCs overall to estimate risk for student pedestrians is a result of a relative lack of pedestrian MVC occurrence in London, which may be indicative of the overall lack of pedestrians. Further, from the available pedestrian MVC data it was not possible to distinguish which MVCs involved school-age children. Future research should integrate hospital emergency room data with police data on MVCs to gain a deeper picture of child pedestrian injury due to MVCs. Nevertheless, while the use of student pedestrian MVCs would allow for a more accurate representation of MVC risk for students, an area deemed hazardous overall still poses a danger to students walking to school.

Another major limitation is the lack of temporal data for built environment variables. This study would have benefitted from temporal built environment data of certain features as it would have been possible to determine the potential causes of MVC hotspot trends in London. Being able to track additions and removals of features like bike lanes, sidewalks, street trees, street lighting and hedges or the widening of roads are examples of dynamic built environment data that would benefit future MVC analysis, could lead to a better understanding of MVCs and therefore more informed policy decisions. Analyzing the changes in cycling infrastructure quality, road widths or crossing guards over time in London could have allowed for more vigorous analysis and potentially more robust conclusions.

Assigning built environment features to mid-block road segments and intersections may seem a trivial task, but is crucial for the accurate representation in spatially explicit models looking at MVC rates associated with built environment features. Future work should consider the varying characteristics of particular road types or intersection types which may necessitate the use of dynamic buffer distances when attributing built environment variables to a certain mid-block segment or intersection. For example, arterial roads and intersections are inherently larger than local roads and intersections, indicating a need for larger buffer distances. Ideally, buffer distances should have a radius large enough to cover all relevant features, but small enough so that it does not attribute features unrelated to that segment or intersection.

Several studies have challenged the use of shortest travel distance in pedestrian route prediction (Sevtsuk & Kalvo, 2022; Lam et al., 2014), with route incongruence found for children walking to school (Buliung et al., 2013). However, a study by Guo and Loo (2013) found that pedestrians in New York City consider travel distance as a major influence on route choice. Additionally, Cooper et al. (2010) found that children tend to use the most direct routes when commuting from home to school. While the overall spatial pattern of student pedestrian flows would likely be quite similar, future work should consider other factors like change in elevation or crossing type in route choice estimation, which could lead to a more accurate representation of actual student pedestrian paths.

The availability of accurate and detailed pedestrian volume data has been a well-documented issue in pedestrian MVC analysis. The focus on student pedestrians allowed for an accurate estimation of student pedestrian volume, however this may be difficult to scale to pedestrians overall. Pedestrian trips often have multiple stops and may be used as transitions between other modes of travel, making it much more complex than a simple home-to-school commute. This poses a significant challenge for future work regarding pedestrian safety and the estimation of overall pedestrian volumes and flows. Greater availability and granularity of data will not only allow for the potential estimation of overall pedestrian volume, but more detailed and nuanced analysis that could lead to more focused interventions and policy decisions.

4.4 Summary

The areas in London with the highest MVC concentrations, posing the greatest risk to all road users, have been identified. Several built environment characteristics of the street network have been shown to have significant effects on the location of these MVC hotspots, namely bike lanes, sidewalks, hedges and on-street parking. Changes to current road design practice and implementation may be necessary to ensure the safety of all road users in London, in accordance with Vision Zero principles. The availability of temporal built environment data would aid future work regarding the trends MVC hotspots are exhibiting. Several areas with high MVC risk in London have been found to also carry large amounts of student pedestrians on their commutes to school. The apparent incongruence of these areas and current crossing guard locations suggests a need for the reassessment of school safety protocols and measures in London. Understanding of the current road safety situation in the City in relation to the most problematic areas and the most vulnerable of road users should inform decisions made on how to address the issue of MVCs.

4.5 References

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