Investigation of Single Bicycle Crashes with a Comparison to Non-Single Bicycle Crashes in Flevoland: A spatial and statistical analysis

Author: Arijana Piljić[a]

Supervisors: Georgios Kapousizis[a], Teun Uijtdewilligen[a,b], Baran Ulak[a], Karst Geurs[a]

[a] University of Twente, Department of Civil Engineering and Management, Faculty of Engineering Technology, Enschede, the Netherlands

[b] SWOV Institute for Road Safety Research, The Hague, The Netherlands

Abstract

This research investigates to what degree built environment factors contribute to single bicycle crashes (SBCs) using police records and ambulance data from Flevoland, the Netherlands, from 2015 to 2021. For this purpose, spatial analysis techniques, including Global and Bivariate Local Moran's I statistics, were applied to identify clustering patterns of SBCs and Non-SBCs. The Network Kernel Density Estimation (NKDE) and Density Ratio Difference (DRD) methods were employed to analyze the density of crashes on road segment level. Lastly, A Negative Binomial Regression (NBR) model was applied to investigate the relationship between built environment factors and the frequency of SBCs and Non-SBCs. The Global and Bivariate Local Moran's I statistics show that both SBCs and Non-SBCs are concentrated in specific areas rather than being randomly distributed, with SBCs notably clustering in rural areas. The Density Ratio Difference (DRD) analysis shows that Non-SBCs primarily occur on roads within urban areas, particularly in city centers. Lastly, the NBR model reveals that a high office- and population density for the area, and a high Mixed Land-Use Areas (MXI), are strongly associated with increased crash frequencies for both SBCs and Non-SBCs. Additionally, Bicycle Kilometers Travelled (BKMT) showed a negative association, while bicycle lanes marked on the carriageway when compared to roads with mixed traffic conditions positively associated with crash frequencies for both SBCs and Non-SBCs. The findings from this research can be used to support the goal of achieving zero traffic-related incidents within Flevoland. Overall, this research identifies crash patterns for SBCs and Non-SBCs, identifies built environment factors contributing to SBCs, and offers recommendations for improving cycling safety by targeting high-risk road segments.

Keywords: Single Bicycle Crashes, Density Ratio Difference, Network Kernel Density Estimation, Negative Binomial Regression

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1. Introduction

Cycling is a practical, environmentally beneficial, and healthy form of transportation (World Health Organization, 2022). Globally, the number of people cycling has increased in the last several decades (Zhang et al., 2023). As more people choose cycling it is necessary to build new and safe cycling infrastructure and improve the quality of the current one (Algurén & Rizzi, 2022). Therefore, it is essential to understand how bicycle crashes occur (Schepers et al., 2015). The occurrence of single bicycle crashes (SBCs) is on the rise (Twisk et al., 2013). However, most studies on cycling safety focus on crashes between motor vehicles and cyclists rather than crashes involving a cyclist falling or hitting an obstacle independently, known as SBCs. Moreover, research by Schepers et al. (2015) shows that between 60% and 95% of cyclists needing hospital admission or emergency department care are victims of SBCs. Aside from direct health risks, SBCs also have direct economic consequences through work absence and productivity losses, and may discourage cycling in general (Schepers et al., 2015).

Due to their frequent exclusion from official road crash statistics, the issue of SBCs has been underreported (Schepers et al., 2015). One reason for this underreporting is the limited data on SBCs, as these incidents are often not reported by the police (Shinar et al., 2018). In contrast, while hospital data is often considered the most reliable source for estimating SBC numbers (Utriainen et al., 2023), it mainly includes crashes where the victim required hospital care and usually lacks detailed crash information, such as the exact crash location. As a consequence, this data is frequently incomplete or missing vital information. These limitations restrict the ability to link crashes to road segments and conduct in-depth analysis on road safety. Although crash characteristics are typically found in police reports the integration of these two data sources is uncommon (Juhra et al., 2012).

In the Netherlands, ambulance data for the province of Flevoland is available as an additional source of crash information (GGD Flevoland, 2022), which includes records from ambulance services and various crash types, including SBCs, documenting incidents where medical assistance was required. Additionally, the national crash database BRON (BRON, 2024) contains police-reported crash data for the entire country. The study of Wijlhuizen & Bos (2020) examined the development of traffic crashes in Flevoland between 2007 and 2018, to identify trends over time and assess the relationships between these different registration systems, using various data sources including BRON, hospital records, and ambulance data. This research found a notable rise in SBCs involving elderly cyclists (aged 60+) in recent years (Wijlhuizen & Bos, 2020). Further emphasizing the need to improve traffic safety to prevent SBCs is a priority discussed in Flevoland's Mobility Vision 2030. In this vision, provincial authorities, in collaboration with road management agencies, set an ambitious goal of achieving zero traffic-related incidents. To accomplish this, the province recognizes the need for a better understanding of traffic safety within Flevoland (Provincie Flevoland, 2016).

This growing need for a better understanding of traffic safety dynamics in Flevoland emphasized the importance of considering the built environment in analyzing SBCs. Since various built-environment factors can impact bicycle crashes

(Abdel-Aty & Radwan, 2000; Saha et al., 2020; Zwerling et al., 2005), the question is whether the same applies to SBCs. However, most existing studies of SBCs focus on crash characteristics, such as road surfaces, infrastructure design, cyclists error, and traffic-related elements (Utriainen et al., 2023), often failing to consider the built environment and the specific locations where these crashes happen. By addressing this gap, the study aims to enhance the knowledge of traffic safety related to SBCs and to inform more effective strategies for improving safety in regions like Flevoland.

To fill this gap and to enhance traffic safety for cyclists in Flevoland, this research aims to examine the specific locations where SBCs occur and investigate how built environment factors —including land-use density (such as office density, mixed land-use areas (MXI), and high streets), population density, proximity to train stations and educational facilities and urban versus rural settings— impact the frequency of SBCs. Furthermore, the bicycle exposure and cycling infrastructure are also analyzed. As studies on the safety of different types of cycling infrastructure are limited in the Dutch context (Uijtdewilligen et al., 2023).

To achieve this a spatial and statistical analysis will be conducted, examining SBCs at macro (PC5) and micro level (road segment). This analysis will use both ambulance and BRON datasets, focusing on the province of Flevoland. The same analysis was applied to other types of bicycle crashes (Non-SBCs) to provide a clearer view of bicycle crash patterns and help identify what specifically affects SBCs compared to Non-SBCs. By addressing this gap, the study aims to enhance the knowledge of traffic safety, related to SBCs, and to inform more effective strategies for improving safety in regions like Flevoland.

The main research question therefore is: "To what degree do built environment factors contribute to SBCs and how do they compare to those affecting Non-SBCs?" To address this question, the study has outlined three sub-questions:

1. What information is available in the BRON and ambulance datasets for SBCs and Non-SBCs, and how do the datasets and the crash types compare?
2. Where do SBCs occur, and how do these locations differ from those of non-SBCs?
3. What is the relationship between built environment factors and the occurrence of SBCs, and how do these relationships differ from Non-SBCs?

Section 2 reviews the academic literature on factors contributing to SBCs. Section 3 outlines the study area and data used. Section 4 explains the methodology for the spatial and statistical analysis. Section 5 presents the analysis results, while Section 6 provides the discussion and Section 7 the conclusions.

2. Literature review

In the literature review there are different factors that are contributing to SBCs (crash factors). These crashes can happen for a variety of reasons and are often underestimated in terms of their frequency and impact on cyclist safety (Utriainen et al., 2023). Understanding the crash factors can help in designing safer environments for cyclists and raising awareness about potential hazards. Based on the literature review, the following categories of crash factors are identified: infrastructure, temporal, individual cyclist characteristics, traffic and built environment related factors.

Infrastructure related factors

The literature suggests that infrastructure-related factors influencing SBCs include the design, condition, and features of roads and cycling infrastructure, such as poor surface conditions, obstacles, road geometry, and inadequate signage, which can increase the risk of crashes. Based on the findings of Utriainen (2020), 62.9% of the SBCs were associated with infrastructure factors. In most of these cases, the crashes were linked to slippery road surfaces, often caused by icy or snowy conditions. This happens due to increased skidding risk on wet road surfaces, attributed to reduced friction between the tire and the road surface (Brown, 2009). Additionally, skidding is more likely to occur in road curves and at intersections, particularly when cyclists are turning (Schepers & Klein Wolt, 2012). Moreover, according to Ormel, Klein Wolt, & Den Hertog (2008) 62% of SBCs occur on straight road sections, about a 20% in a curve, and 6% at an intersection. Materials like mud, sand, and leaves further increase the risk, particularly in curves where this poses the greatest hazard (Schepers, 2008). Although many SBCs result from skidding, there has been limited research specifically focused on this issue. The necessity of studies on slippery road surfaces is debatable, however, as effective infrastructure maintenance could potentially address hazards caused by external materials on the roads (Nyberg et al., 1996).

Road design is another crash factor for SBCs. As SBCs often involve curbstones, such as when cyclists cross or veer off the road and collide with a curb. Additionally, crossing tram tracks or cycling alongside them were identified as situations that could result in SBCs (Gildea & Simms, 2021). This is in line with the result of the study of Schepers (2008) where on bike lanes, the following types of infrastructure-related crashes occurred more frequently: collisions with road narrowing, crashes where a cyclist ends up in a longitudinal groove (rails) and crashes involving bumps, potholes, and objects on the road surface. Schepers & den Brinker (2011) found that certain features of bicycle infrastructure design can contribute to SBCs. Therefore, signs, road markings, and other visual elements of infrastructure should be designed to meet cyclists' needs, taking into account the tasks they perform and how difficult they are.

Moreover, the types of cycling infrastructure where SBCs occur are an important aspect to consider, as around 80% of SBCs happen on streets, bicycle paths, and bicycle lanes or (suggested) bicycle lanes, with other road types accounting for less than 20% (Schepers, 2008). According to Myhrmann et al. (2021) SBCs that occur on standard road sections typically lead to more severe injuries than those happening on bicycle lanes. In the Netherlands, the three most common types of cycling infrastructure are separated bicycle tracks, bicycle lanes marked on the carriageway, and mixed traffic conditions where cyclists share the road with motorized vehicles (Uijtdewilligen et al., 2023). However, Schepers (2008) found that when adjusting for kilometers traveled within urban areas, there is little difference in SBC occurrence between physically separated bicycle paths, bicycle lanes, and roads with mixed traffic. This suggests that the type of infrastructure alone may not have a significant impact on SBC frequency.

It is important to note that a SBC often results from a combination of circumstances, making it difficult to isolate only the infrastructural related factors (Schepers, 2012).

Individual cyclist characteristics related factors

Focusing on crash factors from an individual perspective of the cyclists emphasizes how individual behavior and characteristics of cyclists impact SBCs. According to Ormel, Klein Wolt, & Den Hertog (2008) both younger and older cyclists are at an increased risk of needing emergency care following an SBC, with hospitalization risk especially elevated among the elderly. Moreover, about a quarter of the elderly are hospitalized following SBCs (Ormel, Klein Wolt, & Den Hertog, 2008). Among younger cyclists, men face the highest risk, while among older cyclists, women are most at risk. This suggests that age impacts the types of crashes involving cyclists. Older cyclists are more likely to experience crashes due to physical limitations, especially when mounting or dismounting their bikes. They are also more susceptible to being startled or distracted by other road users, leading to SBCs that often result in serious injuries (Ormel, Klein Wolt, & Den Hertog, 2008).

Several studies have identified bicycle-related factors that play a role in SBC occurrences (Boele-Vos et al., 2017; Ohlin et al., 2019; Utriainen, 2020). These issues include instances of hard braking resulting in the cyclist falling over the handlebars or losing control, as well as crashes occurring during mounting or dismounting, or at slow speeds. Moreover, Schepers (2008) concludes that nearly half of all SBCs are partly caused by an action of the cyclist themselves. Speed is a crucial factor in SBCs, posing risk factors at both low and high speeds. At low speeds, more effort is required to stabilize the bicycle, particularly during mounting or dismounting while at high speeds skidding and imbalance are more likely to occur (Schepers & Klein Wolt, 2012). Therefore, the study of De Rome et al. (2014) argue that safety improvement strategies should incorporate essential skills for bicycle handling and riding. However, despite the emphasis on skills, it is worth noting that injuries from SBCs often occur among experienced cyclists who regularly engage in cycling (Beck et al., 2019; Hertach et al., 2018), suggesting that lack of cycling skills may not be the main cause. However, cyclists who ride infrequently (less than once a week) are at a higher risk of experiencing a crash that appears to correlate with their cycling abilities and physical strength: falling while mounting or dismounting, and losing control due to braking errors. The study of Heesch et al. (2011) offers further insights, revealing that individuals who had engaged in cycling for less than five years were reporting more injuries resulting from bicycle crashes. This indicates that the conclusion for SBCs differs from that of regular cycling crashes.

Bicycle defects are also classified under cyclist-related factors, as issues like faulty wheel gears or broken chains, which result from poor maintenance or oversight, can contribute to SBCs (Schepers & Klein Wolt, 2012).

Temporal related factors

Temporal factors also play a role in the occurrence of SBCs. According to Ormel, Klein Wolt, & den Hertog (2008), the risk of SBCs is higher at night (between 12:00 AM and 6:00 AM) and during weekends, with the highest risk occurring on weekend nights. Furthermore, SBCs that happen after dark are more likely to result in severe injuries (Myhrmann et al., 2021). This may be attributed to the influence of alcohol consumption, which is known to be a contributing factor to SBCs (Møller et al., 2021).

Seasonality is also an important factor, as Utriainen (2020) found that winter conditions contribute to 81% of SBCs during that season, compared to 44% during other seasons. Notable is that in non-winter months, factors related to the cyclist, the bicycle itself, and interactions with other road users are more prevalent. However, Reurings et al. (2012) reported that the risk of cyclists sustaining serious injuries in SBCs is higher in summer than in winter. This contrast may suggest that SBCs are more frequent in colder countries, like Sweden, Finland, and Norway, where snow and ice are common, compared to regions with milder winters (Utriainen et al., 2023).

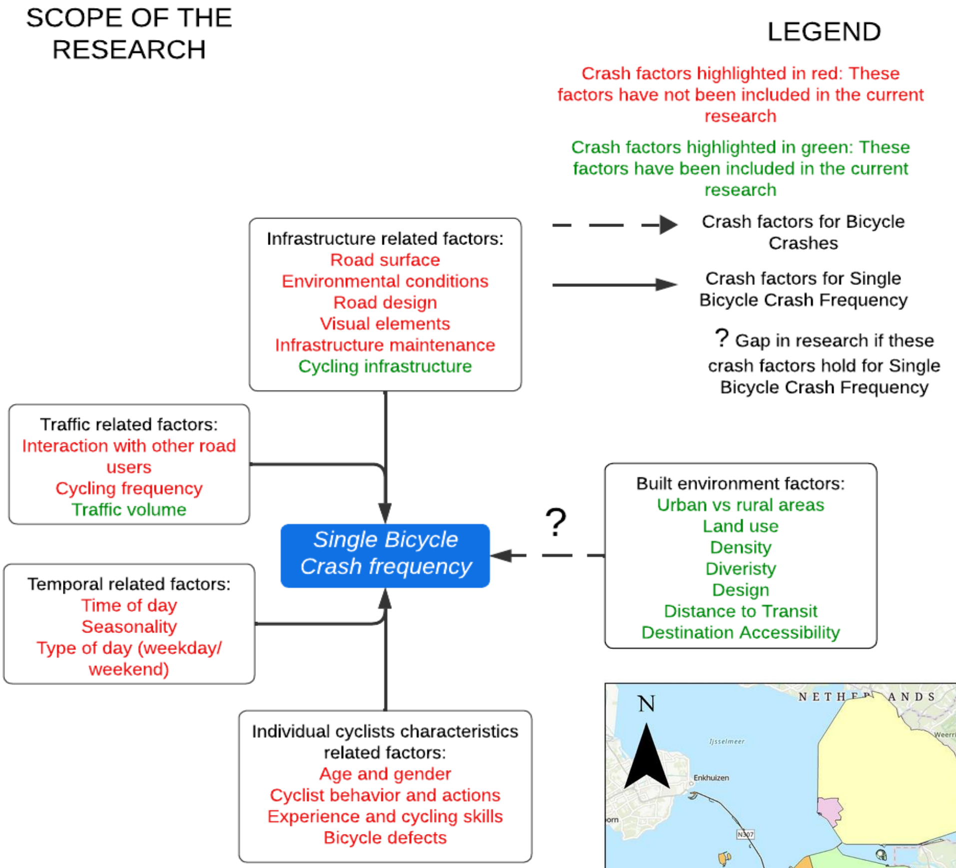
Traffic related factors

Traffic-related factors also play a crucial role in the frequency and severity of SBCs. Research has shown that SBCs are more likely to result in severe injuries on roads with low traffic volume and fewer cyclists (Myhrmann et al., 2021). In terms of cycling frequency, Schepers (2012) found that as bicycle use increases, the risk of experiencing an SBC per kilometer traveled decreases. In contrast to the earlier results found in Heesch et al. (2011). This phenomenon, often referred to as the "safety in numbers" effect, suggests that higher levels of cycling contribute to greater awareness and caution from other road users, ultimately reducing the likelihood of crashes (Elvik & Bjørnskau, 2017). However, this increased volume of bicycles alone may not fully account for the higher frequency of SBCs. Even with the "safety in numbers" effect, which suggests that more cyclists can lead to greater awareness and fewer crashes, SBCs can still occur due to interactions with other road users. Cyclists might fall while swerving or braking to avoid a vehicle, lose sight of obstacles due to a vehicle in front, or be distracted by the behavior of someone behind them (Davidse et al., 2014). However, the relationship between the frequency of SBCs and the prevalence of cycling within a population is not straightforward. Schepers et al. (2015b) found that the ratio of injured cyclists involved in SBCs does not correlate directly with the percentage of cycling in the modal split. As the percentage of cycling within the modal split increases, the proportion of SBC-related casualties rises more slowly compared to the overall increase in cycling activity. This suggests that although more cycling leads to a greater number of cyclists on the road, the increase in SBC-related injuries is disproportionate and does not mirror the overall rise in cycling participation.

Built environment related factors

Factors related to the built environment have been widely studied in cycling safety, with much attention on how they affect the number of bicycle crashes (Chen, 2015; Narayanamoorthy et al., 2013; Wei & Lovegrove, 2013). Research shows that crash frequencies are generally higher in urban areas compared to rural ones (Abdel-Aty & Radwan, 2000; Zwerling et al., 2005), largely due to more complex traffic conditions and travel demand factors like higher traffic volumes, congestion, and poorer road conditions (Jiang et al., 2011). Studies on factors surrounding land use have produced mixed result. Some studies (Narayanamoorthy et al., 2013; Vandenbulcke et al., 2014) found more bicycle crashes in areas with increased commercial land use, while others reported that commercial and educational zones pose safety risks for cyclists (Mukoko & Pulugurtha, 2020; Osama & Sayed, 2017). In contrast, Strauss & Mirando-Moreno (2012) did not find commercial land use to be a significant predictor, showing inconsistencies may be due to variation in urban layout across regions. An example of this is the historic, winding streets of European cities as opposed to the grid-like structure of North American cities.

Another key built environment element is the presence of high streets, which are typically defined as the main commercial and retail areas in cities or towns. These streets are characterized by a high density of shops, restaurants, cafes, and other service-oriented businesses, making them hubs of social and economic activity. High streets also tend to see higher levels of cycling and public transport use due to their central location and mixed land use. In the study of Kapousizis et al. (2021), high streets were identified based on specific Points of Interest (POIs), such as retail stores, dining establishments, educational and health services, entertainment venues, and commercial services. The study found that high streets were associated with a significantly increased risk of cycling-related injuries, even after adjusting for other factors like road type and traffic infrastructure.



The literature review on SBCs reveals that most studies overlook the built environment, which is a crucial factor in bicycle crashes. Built-environment factors are often represented by the "5Ds" indicators, namely: density, diversity, design, distance to transit, and destination accessibility (Ewing & Cervero, 2010). Therefore, this study aims to address this gap by exploring the influence of built environment characteristics—such as land use, and population density—on SBC frequency.

Figure 1 summarizes the scope of this research. This research investigates crash factors represented in green as shown in the figure, while those in red indicate factors that are not investigated. Notably, a gap exists regarding the applicability of crash factors from broader bicycle crashes to SBCs, which will be addressed in this research.

3. Data

3.1 Study area

This research focuses exclusively on the province of Flevoland and its cycling network. The area was chosen due to the availability of ambulance data. Located in the center of the Netherlands, Flevoland is the newest and, in terms of land area, the smallest of the twelve provinces (Provincie Flevoland, 2024). As the newest province, Flevoland's infrastructure has been developed more recently and can therefore influence traffic patterns. Its modern infrastructure, along with relatively new network and urban structures, makes it particularly relevant for studying how these factors impact traffic patterns compared to older Dutch areas and cities.

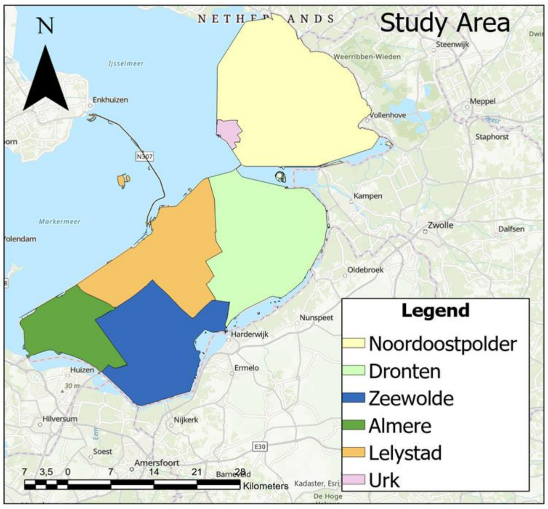


Figure 2: Study area Flevoland

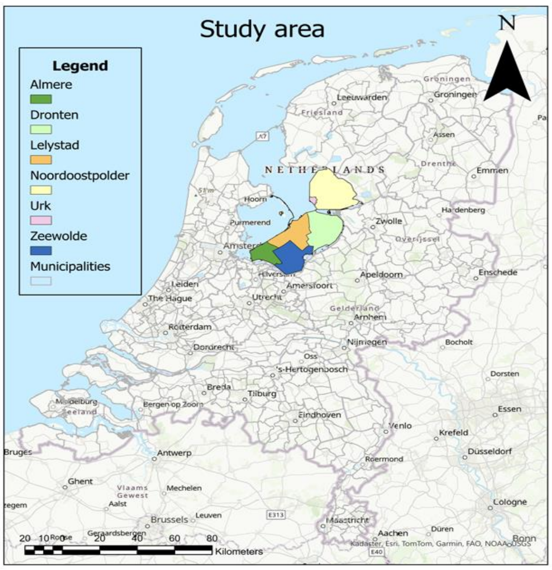


Figure 3: Study area within the Netherlands

The province of Flevoland contains six municipalities: Almere, Dronten Lelystad, Noordoostpolder, Urk and Zeewolde. As of 2024, the province has a population of 450,826 people and 191,491 households (Provincie Flevoland, 2024). Figure 2 presents the study area, highlighting the six municipalities, while Figure 3 provides an overview of these municipalities and their locations within the Netherlands.

3.2 Crash datasets

3.2.1 Ambulance dataset

One of the two crash datasets used in this study is the Ambulance dataset, which covers ambulance records for the province of Flevoland from 2015 to 2021. This dataset reports 2,437 bicycle crashes and includes details such as the year, victim and opposing party, municipality, latitude and longitude, junction identification (JTE_ID), and road segment identification (WVK_ID). The location recorded in the dataset represents the position where the ambulance was stationed, rather than the exact location of the crash. As a result, the crash data points were spatially joined to the closest road segment.

From the Ambulance dataset - see Figure 4 – it is shown that in the year 2018 there is a notable peak in both Non-SBCs and SBCs, suggesting a possible surge in bicycle related crashes during that period. Conversely, 2021 exhibits a decline in Non-SBCs but an increase in SBCs, indicating shifting trends in the nature of bicycle crashes over time, possibly due to the effects of COVID-19 (Francke, 2022).

Variations in the frequencies of SBCs and Non-SBCs across the municipalities of Flevoland reflect differing crash frequencies among these areas. In more urban municipalities such as Almere and Lelystad, both Non-SBCs and SBCs are higher compared to the more rural municipalities, see Figure 5.

Since reliable data on mobility by municipality in Flevoland is unavailable (Wijlhuizen & Bos, 2020), the number of crashes per 100,000 inhabitants as a measure to compare crash frequencies across municipalities was used. This approach helps normalize the data, allowing for fairer comparisons between areas with different population sizes. The results showed that Almere has the highest rate of SBCs per 100,000 inhabitants, while Lelystad has that in Non-SBCs.

It is important to consider that the length of the road network within a municipality can also be a contributing factor (Wijlhuizen & Bos, 2020). Almere and Zeewolde have limited areas within their municipal boundaries, whereas other municipalities such as Zeewolde and Noordoostpolder consist of a relatively small core with a much larger surrounding area intersected by roads. Figure 7 shows this difference between Almere and Zeewolde.

3.2.2 BRON dataset

The second crash dataset used is the BRON dataset, the Registry of Traffic Accidents in the Netherlands, which includes records of traffic crashes reported by the police throughout the country. A traffic accident is defined as an "incident on a public road involving traffic that causes damage to property or injury to individuals, with at least one moving vehicle involved (Rijkswaterstaat, 2022).

The dataset used in this research consisted of 427 crashes involving at least one bicycle, excluding Property Damage Only (PDO) crashes due to poor data quality. BRON provides detailed information on the accident, including the type of crash and time. It also includes data on the driver and victims, such as age and gender, the road—covering location, condition, and situation—surroundings such as lighting, weather conditions, the season, and the maximum speed limit.

Within the BRON dataset, Urk and Noordoostpolder have the highest number of bicycle crashes per 100.000 inhabitants (see Figure 4 and Figure 6). Over the years, a noticeable increase in SBCs is observed in the BRON dataset from 2017 onward, likely due to enhanced registration of this type of crash (see Figure 5).

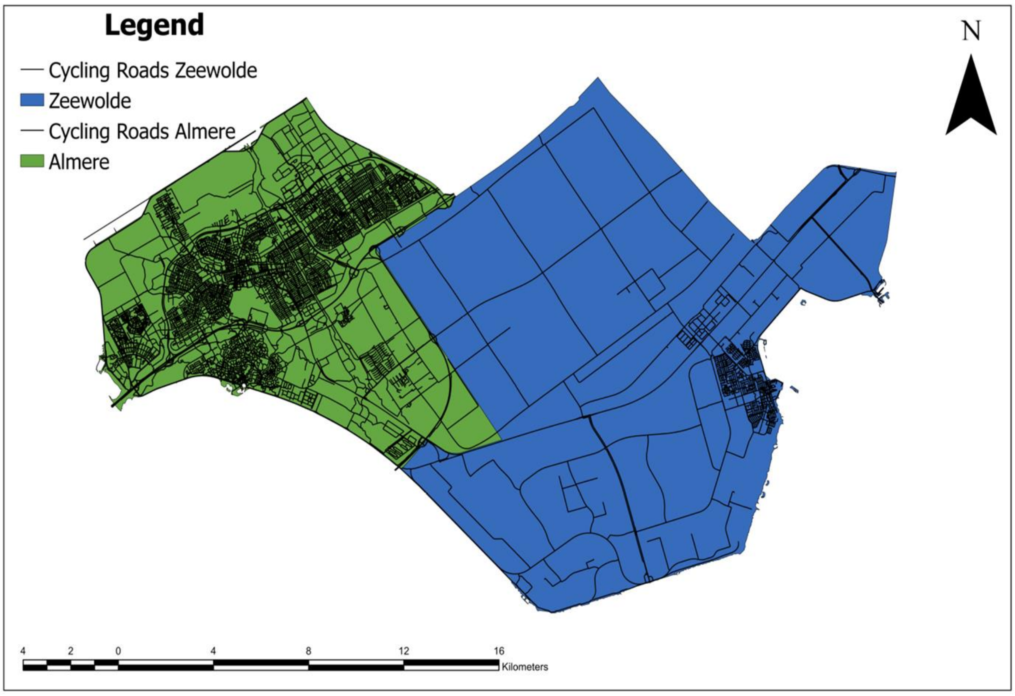


Figure 7: Almere and Zeewolde and cycling roads

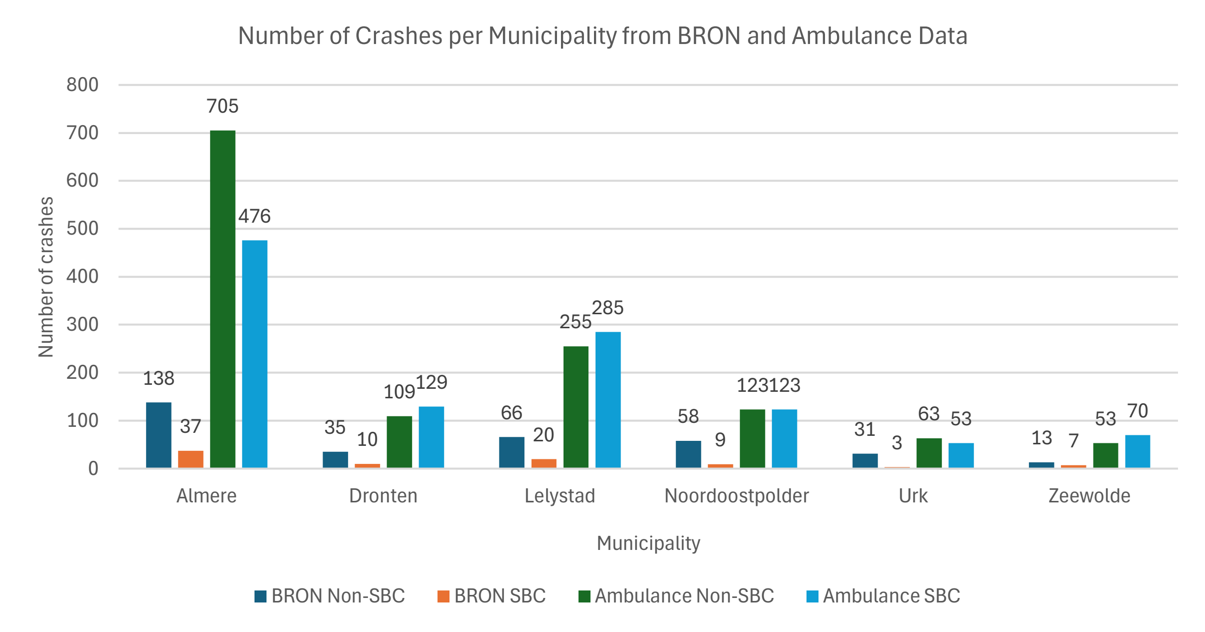


Figure 4: Number of crashes per municipality

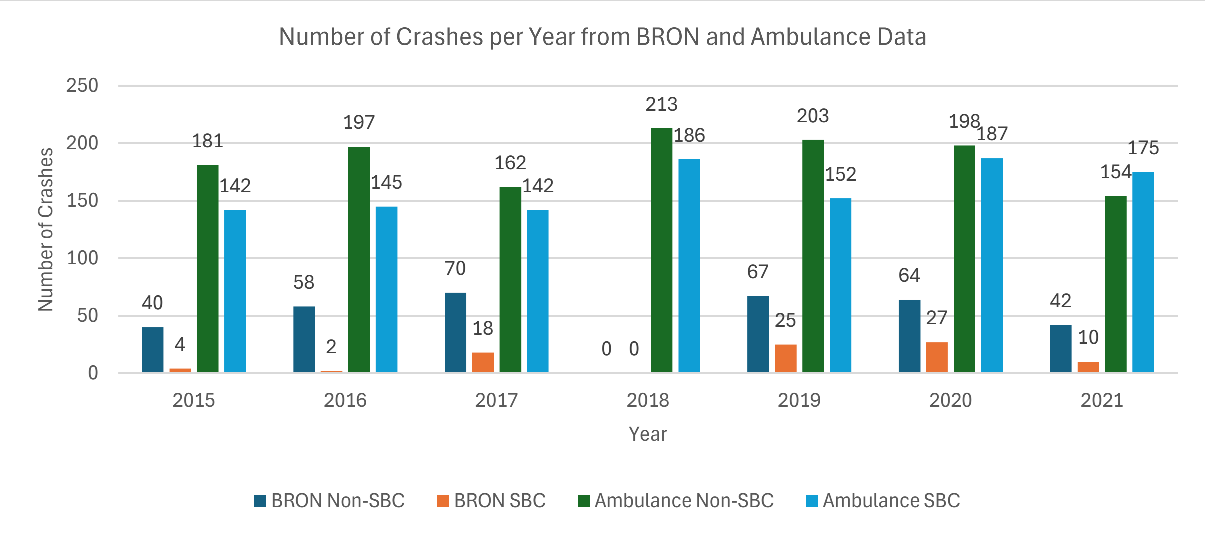


Figure 5: Number of crashes per year

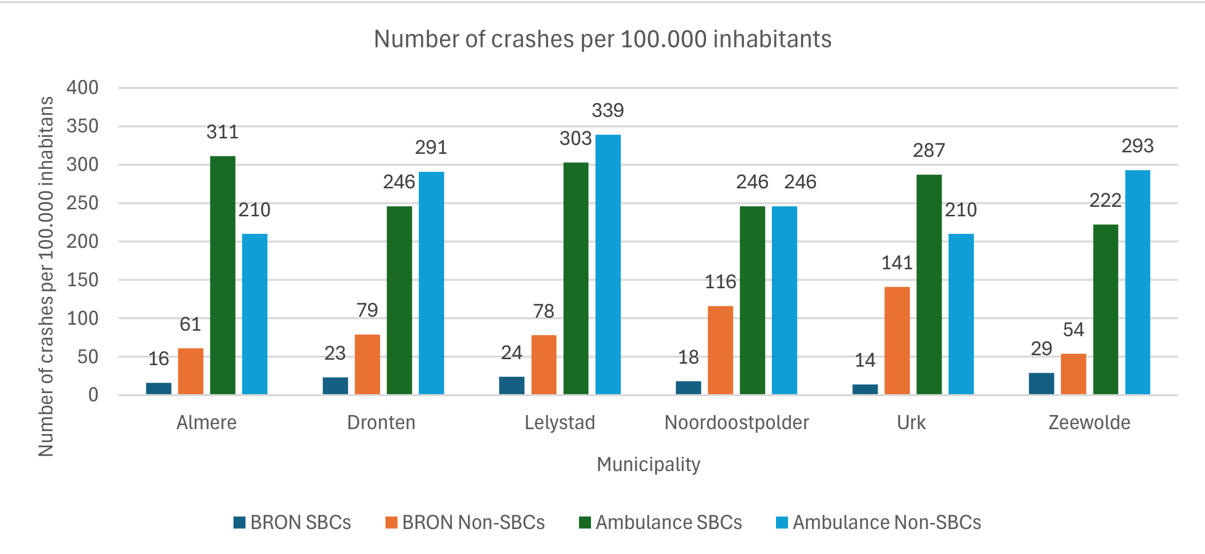


Figure 6: Number of crashes per 100.000 inhabitants

3.3 Units of analysis

Traffic safety analysis can be conducted at two levels: macroscopic and microscopic (J. Lee & Abdel-Aty, 2018). This study examines both levels. At the macroscopic level, PC5 zones—five-digit postal codes in the Netherlands that represent specific geographic areas—are used to provide a broad overview of data within Flevoland. This level helps to analyze differences between SBCs and Non-SBCs by enabling a more detailed spatial understanding of crash patterns and identifying areas with distinct safety concerns within Flevoland. There are 917 PC5 zones in Flevoland. PC5 zones were selected over PC4 and PC6 because they provide the optimal level of detail for this analysis, with PC4 being too broad and PC6 too detailed. As a result, PC5 will be used as the unit of analysis for the spatial autocorrelation.

For the microscopic level the road segment was chosen because it allows for a more detailed and precise examination of where SBCs and Non-SBCs occur. Therefore, for the spatial and statistical analysis, the road segment will serve as a unit of analysis.

Each road segment has an unique identifier (WVK_ID) which is provided from the National road database (Nationaal Wegenbestand (NWB)) (NWB, 2024), and the Dutch Cyclists' Union data (Fietserbond) has been spatially joined to this WVK_ID, resulting in the inclusion of 19,618 road segments in this study. The study will focus on roads that are accessible to bicycles, road segments where cycling is not allowed are excluded from this study. These road segments are then classified into three types of cycling infrastructure: 1) mixed traffic conditions, 2) bicycle lanes marked on the carriageway and bicycle streets and, 3) separated bicycle tracks. The classification was primarily based on the Fietsersbond dataset, which covers most road segments, were any missing classifications were supplemented by the NWB road classification. Figure 8 shows the number of crashes occurring across different types of cycling infrastructure. It is clear that the majority of crashes take place on roads with mixed traffic conditions.

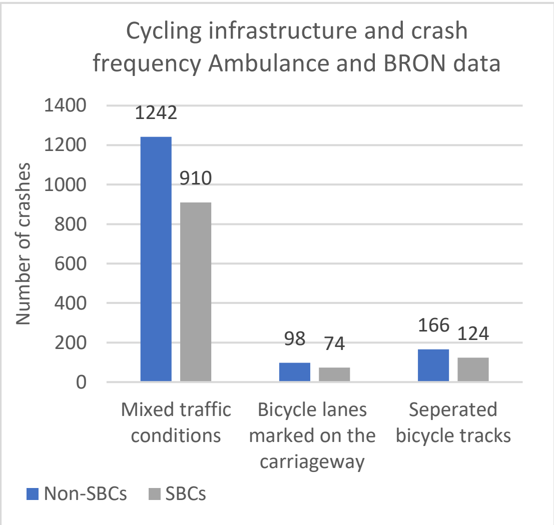


Figure 8: Cycling infrastructure and crash frequency for Ambulance and BRON Data

Furthermore, the density of SBCs and Non-SBCs on cycling infrastructure is shown in Table 1.

Table 1: Cycling infrastructure with road segment length and density

Cycling infrastructure	Total road segment length (KM)	Average road segment length (KM)	Density Non-SBCs (Total road segement length (KM)/ Number of Non-SBCs)	Density SBCs(Total road segement length (KM)/ Number of SBCs)
Mixed traffic conditions	2043.07	0.13	1.64	2.25
Bicycle lanes marked on the carriageway	287.01	0.23	2.93	3.88
Seperated bicycle tracks	363.72	0.17	2.19	2.93

Notable is that bicycle lanes marked on the carriageway have the highest density of crashes, with 2.93 for Non-SBCs and 3.88 for SBC. Mixed traffic conditions have the longest total length but lower density, at 1.64 and 2.25, respectively. This shows that, despite the greater total road length in mixed traffic conditions, the density of crashes is higher on bicycle lanes and separated bicycle tracks.

3.4 Bicycle intensities in Flevoland

The bicycle intensities for Flevoland are provided by Dat.mobility, a division of Goudappel, which uses the traffic model 'OmniTRANS Spectrum'. This traffic model calculates the bicycle intensities for 2023 on each road segment. Using the midpoint of the bicycle intensities for each road segment, the segment was spatially joined with the WVK_ID.

In Figure 9 the frequency of the bicycle intensity is shown. The histogram shows that most bicycle traffic occurs at low intensities, with 13,530 road segments (WVK_ID) in the [0, 100] range, with 1,641 road segments having zero bicycle frequency. Higher intensities become less common, with just 221 road segments exceeding 1,600. This indicates that low bicycle intensities dominate, while high bicycle volumes are rare.

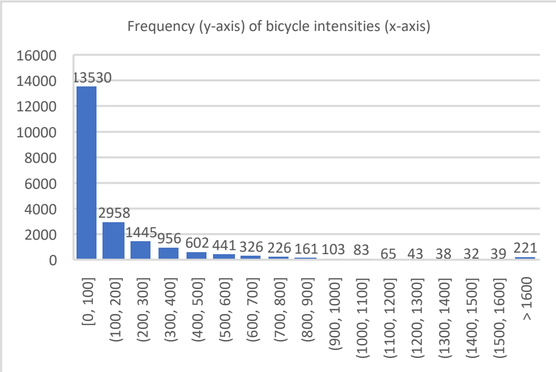


Figure 9: Frequency of the bicycle intensities

Motorized volume could not be included in this study because of data limitations on minor roads within the VENOM model.

3.5 Variables used in the statistical model

The variables bicycle intensity, cycling infrastructure, speed limit, population density, households, proximity to trainstation and educational facilities, urban area, highstreet and land-use variables (residential areas, gathering spaces, prisons, healthcare facilities, industrial areas, offices, lodging, transportation, sports, retail, and mixed land-use index (MXI)), were used for the statistical model.

For the built environment data (population density, households, and land-use variables), a 200-meter buffer was created around each road segment. The width of the buffer used to extract land-use variables should correspond to typical cycling distances in the study region. In this case, a 200-meter buffer was chosen to capture the relevant surrounding environment for cyclists.

Within this buffer, a 100x100 meter grid was generated, and the land-use variables were divided into these grid cells. There is assumed in this research that the values of the land-use variables are evenly distributed across the area. As a result, each 100x100 meter cell contains data if this was available. The closest grid cells were then spatially joined to each road segment to assign land-use variable data to each road segment. For a visual representation refer to Figure 10. The same approach was applied to population density and household data; however, since this data was already available in 100x100 meter grid cells, it was directly linked to the road segments. This data did not extend beyond the roads within the specified buffer area.

Pearson correlation was used to test for multicollinearity in the population density, households and land-use variables (Vahedi Saheli & Effati, 2021) which revealed a high correlation between population density and households, as well as most of the land use variables. As a result, only population density was used for this study and households were excluded. Offices and mixed land-use index (MXI) were included, as they did not exhibit high correlation. Similarly, categorical variables were tested for correlation using the chi-square test, leading to the removal of the speed limit variable due to its strong correlation with cycling infrastructure.

Figure 10: Road segments with buffer

To capture the level of activity on a road segment, high streets were modeled. Therefore, the model assesses points for shops, meeting places, offices, industries, accommodations, healthcare facilities, and sports centers. A road segment is classified as a high street if at least 8 of these points are within a 50-meter radius of each other and within a 200-meter buffer of the road.

Educational facilities and train stations were mapped as points, and road segments within 150 meters of these points in terms of network distance (Uijtdewilligen et al., 2023; Ulak et al., 2018) were modelled as road segments that are close to these facilities. Lastly, whether a road segment was located in an urban area was determined using the NWB urban boundaries. Any missing values were filled in by visually referencing the ESRI shapefile of the urban boundaries in ArcGIS Pro. Table 2 displays the descriptive statistics of these variables and Table 3 shows the sources and variables used in this research.

Table 3: Sources and variables used

Crash factor	*Dataset*	*Variables*	*Use*
	BRON	Bicycle crash data	For the frequency, location, and details of the crashes
	Ambulance	Bicycle crash data	For the frequency, location, and details of the crashes
Traffic volume	OmniTRANS	Bicycle volumes	For the bicycle intensities for each road segment
Density	CBS	Population	For the population and in each 100 x 100 cell
Land use diversity	CBS	Land use	For the land use variables within each 100 x 100 cell
	CBS	PC5	Analysis unit
Design	Kadaster	Highstreet	To allocate clusters of buildings to a road segment
Destination accessibility	Kadater	Educational facilities	To designate educational facilities to road segments that are accessible within 150 meters
Distance to Transit	Esri Nederland	Trainstation	To designate train stations to road segments that are accessible within 150 meters
	NWB	Road network	For the road segment identification (WVK_ID)
Urban vs rural areas	NWB/ Urban shapefile	Urban	Decides if a road segment is in a urban area
	NWB	Road segment length	The variable to be multiplied with bicycle intensities for the BKM
Cycling infrastructure	Dutch Cyclist's Union/ NWB	Cycling infrastructure	For assigning the cycling infrastructure for each road segment

Table 2: Descriptive statistics of the variable

Variables	**Description**	**Mean**	**Standard deviation**	**Min**	**Max**	**Total of variable**
SBC	Number of SBCs	0.06	0.25	0	2	1,108
Non-SBCs	Number of Non-SBCs	0.08	0.35	0	4	1,506
BKMT (Bicycle kilometers travelled)	Log(total daily bicycle intensities*road segment length)	18.82	63.97	0	1,824	369,307
Mixed traffic conditions (reference category)	If road segment is a road with mixed traffic conditions (1=yes;0=no)	0.83	0.38	0	1	16,242
Bicycle lanes marked on the carriageway	If road segment has bicycle lanes marked on the carriageway (1=yes;0=no)	0.06	0.25	0	1	1,263
Seperated bicycle tracks	If road segment has separated bicycle tracks (1=yes;0=no)	0.11	0.31	0	1	2,113
Urban	Urban area or rural area (1=yes;0=no)	0.95	0.22	0	1	18,571
Highstreet	If road segment is a highstreet (1=yes;0=no)	0.07	0.25	0	1	1,368
Education facility	If road segment is within 150 meters from educational facility (1=yes;0=no)	0.12	0.33	0	1	2,358
Trainstation	If road segment is within 150 meters from train station (1=yes;0=no)	0	0.05	0	1	51
Population Density	Density of population at road segment	69.66	0.33	1	406	258,569
MXI	Mixed land-use index at road segment	21.66	56.25	0	2,420	424,812
Office Density	Density of offices at road segment	38.20	130.45	0	3,807	749,623

4. Methodology

This section details the methodologies applied to analyze crash data, identify spatial patterns, and model the risks associated with SBCs and Non-SBCs. The analysis encompasses three main aspects: differences in datasets and contributing factors (4.1), spatial autocorrelation (4.2), and spatial analysis using network-based methods (4.3). A statistical model was also developed to predict crash occurrences based on a range of contributing variables (4.4).

4.1 Descriptive statistics of BRON data

The BRON dataset was analyzed to investigate the number and percentages of crash factors based on various attributes: cyclist age, gender, crash location, whether the crash occurred at an intersection, road conditions (dry or wet), presence of street lighting, road layout (straight road, curve, roundabout, 3-branch intersection, 4-branch intersection), time and day of the crash (weekday or weekend), season, lighting conditions (daylight, darkness, twilight), weather (dry or rainy), and the road's maximum speed limit.

4.2 Spatial autocorrelation

To compare the spatial distribution of SBCs and Non-SBCs using both ambulance and BRON data, spatial autocorrelation tests were conducted, starting with the Global Moran's I test. This test was used for identifying spatial clusters and patterns, helping to determine how nearby crashes influence each other and revealing spatial patterns across different datasets and crash types. Specifically, Global Moran's I was used to assess whether crashes were spatially clustered across the study area. The index ranges from -1 to +1, with positive values indicating clustering, negative values suggesting dispersion, and zero reflecting a random distribution (Gedamu et al., 2024). Typically, Moran's I is converted into a Z-score, where positive scores indicate similar nearby values and negative scores indicate dissimilar nearby values (Siddiqui et al., 2014). For this analysis, a ".swm" file was used to capture and store the spatial relationships between crash points within the network, providing a clearer understanding of connections between locations for more precise accident analysis (Ermagun & Levinson, 2018), as real-world travel networks are more suitable for this type of analysis (ESRI, 2024c) and this research.

To identify high-risk zones in Flevoland and distinguish between areas where SBCs and Non-SBCs clusters occur, Local Moran's I was applied after calculating Global Moran's I. This approach assesses local clusters for similarity or dissimilarity and helps determine the presence of spatial autocorrelation at the local level, revealing patterns of concentration or dispersion in crash occurrences. In this approach the clusters were visualized with LISA maps, revealing four types of cluster zones: High-High (HH), High-Low (HL), Low-High (LH), and Low-Low (LL) (Erdogan, 2009). Positive values indicate clustering of similar features (HH and LL), while negative values suggest dissimilar features (HL and LH) (Zandi et al., 2023). Since Local Moran's I doesn't need to handle crashes on a network in this part of the study, there is no need to use spatial weight matrices to understand spatial relationships. Therefore, crashes were aggregated at the PC5 level, and the optimal threshold distance was determined using 'Incremental Spatial Autocorrelation'. Outliers were excluded to ensure that features remained connected. For a detailed explanation of this methodology, please refer to the Appendix I.

Local Moran's I was used to identify areas of local clustering. To further explore the differences in clustering patterns between SBCs and Non-SBCs, Bivariate Local Moran's I was employed. This analysis helps determine whether certain locations are prone to both types of crashes or if they tend to occur in distinct areas. Bivariate Local Moran's I is an extension of Local Moran's I that measures the spatial association and clustering patterns between two variables (S.-I. Lee, 2001). In this research, Bivariate Local Moran's I will be used to analyze the relationship between spatial clusters of SBCs and Non-SBCs within each dataset, with the goal of investigating differences between these crash types using the "Bivariate Local Moran's I" tool in GeoDa software.

4.3 Spatial analysis

A spatial analysis was conducted to find SBC hotspots and identify the most dangerous roads for these crashes. As this study aims to investigate crashes on the road network the Network Kernel Density Estimation (NKDE) was used to locate the riskiest roads for SBCs in Flevoland, and the results were compared to the most dangerous roads for Non-SBCs.

NKDE is a spatial analysis method designed to estimate the density of point events along network structures such as roads or railways. Unlike traditional Kernel Density Estimation (KDE), which applies to two-dimensional space, NKDE adapts KDE to network data by considering the influence of each point along network distance rather than in Euclidean distance (Thakali et al., 2015). For instance, a 1 km bandwidth in NKDE means each point's influence extends 1 km along the shortest network path (Mohaymany et al., 2013). This method is especially useful for analyzing phenomena like traffic crashes, crime incidents, or utility failures along networks (Thakali et al., 2015).

The NKDE was generated using the "Kernel density estimation" function which was provided by the Spatial Analysis Along Network toolbox (SANET). It was used to identify high-density segments and to test the clustering of the crashes, which were subsequently visualized as density maps. Here, the road network shapefile covering the entire study area serves as the input layer, while crash data points (SBCs and NSBCs) were utilized as kernel points. The equal-split continuous kernel function was used. Okabe et al. (2006) outlines the benefit of this function, emphasizing its ability to reduce computation time, especially when dealing with complex networks. The use of this type of function requires the selection of a bandwidth. According to Lakshmi et al. (2019) the selection of bandwidth is subjective and relies on the study area's scope. Typically, a narrower bandwidth range yields a more precise density estimate, effectively capturing all peaks and valleys. Conversely, a broader bandwidth range generates a smoother distribution, leading to reduced detection of variations (Thakali et al., 2015). A bandwidth of 500 meters was determined based on the size of the study area and the distribution of SBCs, with bandwidths between 20 and 1000 meters being prevalent for this type of problem (Blazquez & Celis, 2013; Erdogan et al., 2008; Ha & Thill, 2011; Keskin et al., 2011; Xie & Yan, 2008). Cell widths are typically selected to be 1/10th of the bandwidth (Okabe et al., 2006), and therefore a cell width of 50 was chosen.

To compare crash densities of the SBCs and Non-SBCs from the NKDE the "Density Ratio Difference" (DRD) parameter was used. The DRD is the difference between the crash densities for two different groups after they have been normalized to their maximum values (Ulak et al., 2017). The formula for DRD is shown in the following equation:

$$DRD_{ij} = \frac{D_i}{\max(D_i)} - \frac{D_j}{\max(D_j)}$$

Here, DRD_{ij} represents the "density ratio difference" between maps i and j. D_i and D_j are the density values of the corresponding roadway sections, while $\max(D_i)$ and $\max(D_j)$

are the maximum crash density values of the compared maps, respectively (Ulak et al., 2017).

4.4 Statistical analysis

A variety of statistical techniques have been used for crash prediction and modeling. Crash Prediction Models (CPMs) are essential for traffic safety, as they help identify and analyze the relationships between crash frequency and the contributing factors involved (Naghawi, 2018). Since crash numbers are non-negative integer counts, a regression model suitable for count data is necessary (Lord & Mannering, 2010). The Poisson model is typically employed when the data is not over-dispersed; however, the crash data in this research is demonstrating over-dispersion. Moreover, the data showed to have sufficient information to assess the zero counts, showing that the number of observed zeros was not greater than the number of predicted zeros. This led to the use of a Negative Binomial regression model, which is more appropriate for addressing such issues. Therefore, the Negative Binomial Regression (NBR) model, which accounts for over-dispersion, will be used in this study. The NBR extends the Poisson model by incorporating a gamma distribution to address the additional variability (Lord & Mannering, 2010). Therefore, the equation for the expected number of crash counts in this research is as follows:

$$\lambda_i = \exp\left(\beta X_i + e_i\right)$$

where λ_i represents the expected crash frequency at road segment i, X_i represent a vector of explanatory variables, β is a vector of parameters to be estimated, and e_i is the error term, which follows a Gamma distribution (Lord & Mannering, 2010).
The final crash model was constructed as a multiplicative model (Hauer, 2004). In these models, the impact of predictors on crash outcomes is more accurately represented by multiplicative factors rather than additive ones (Uijtdewilligen et al., 2022). The final model for this study is expressed as follows:

$$E(Y) = BKMT^{\beta_1} * \exp(\beta_{0+}\beta_{n+1}x_n)$$

Where, E(Y) is the expected frequency of SBCs or Non-SBCs. BKMT (Bicycle Kilometer Travelled) = Bicycle intensities × road segment length represents the exposure term for each road segment (WVK_ID). The x_n represents the categorical variables and the β denotes the coefficients to be estimated.

In the model, the dependent variables are the counts of SBCs and Non-SBCs. Furthermore, the model incorporates several variables to assess road segments. The bicycle intensity is used as an exposure variable and is multiplied by the road segment length to account for the level of bicycle traffic in relation to the size of the road segment to get the variable Bicycle Kilometer Travelled (BKMT). Additionally, the model includes one categorical variable: cycling infrastructure. Here, road segments with mixed traffic conditions serve as the reference category, while the other two types of cycling infrastructure—roads with bicycle lanes marked on the carriageway and separated bicycle tracks—are the explanatory variables. The model also considers whether a road segment is in an urban area, assigning a value of 1 if it is, and 0 if it is not. To identify highstreets, road segments designated as highstreets are assigned a value of 1, while all other segments receive a value of 0. Educational facilities and train stations are mapped as points, and road segments within 150 meters of these points in terms of network distance (Uijtdewilligen et al., 2023; Ulak et al., 2018), receive a value of 1; otherwise, they receive a 0. Lastly, the population density and land-use variables are treated as continuous variables in the model.

5. Results

5.1 Descriptive statistics of BRON data

The descriptive statistics of the BRON dataset are categorized in infrastructure, individual cyclists characteristics and temporal related factors and are shown below in Table 4,5, and 6. The color green indicates the outcome within a factor (e.g. road condition) where the fewest crashes occur, red represents the highest, and yellow signifies all values in between. It is notable that Non-SBCs often have a higher proportion of unknown data compared to SBCs, particularly regarding age, gender, and day of crash, indicating less detailed reporting compared to SBCs. This difference in reporting may be attributed to variations in injury severity, the type of road user, and the location of the crash (Alsop & Langley, 2001).

5.1.1 Infrastructure related factors

Table 4 shows that crashes of both types mostly occur under dry road conditions and that both SBCs and Non-SBCs often occur when the road light wasn't burning. Furthermore, the analysis reveals that SBCs and Non-SBCs are more likely to occur in urban areas. The data indicates that SBCs are mostly observed on straight roads, while Non-SBCs are more common at intersections, especially 4-way intersections. This suggests that SBCs are less likely to occur at complex intersection points and are more frequent on straightforward road segments. This is in line with the study of Ormel, Klein Wolt, & den Hertog (2008), where 62% of SBCs occur on straight sections, about 20% on curves, and 6% at intersections. However, Schepers & Klein Wolt (2012) argue that skidding is more likely in road curves and at intersections, especially when cyclists are making turns. Additionally, Non-SBCs are generally associated with roads that have higher speed limits (50 km/h), while SBCs are more commonly found on roads with lower speed limits (30 km/h).

Table 4: Infrastructure related factors

Factors	**SBC**		**Non-SBC**	
	n	(%)	n	(%)
Infrastructure related factors				
Location of the road	86	100	341	100
Urban	55	64	292	86
Rural	20	23	45	13
Unknown	11	13	4	1
On intersection	86	100	341	100
Yes	23	27	239	70
No	63	73	102	30
Road condition	86	100	341	100
Dry	55	64	246	72
Wet	19	22	85	25
Unknown	12	14	9	3
Road light	86	100	341	100
Yes	8	9	31	9
No	49	57	267	78
Not present	13	15	33	10
Unknown	16	19	10	3
Road situation	86	100	341	100
Straight road	41	48	85	25
Curve	9	10	11	3
Roundabout	2	2	26	8
3-branch intersection	10	12	57	17
4-branch intersection	12	14	157	46
Unknown	12	14	5	1
Max speed (km/h)	86	100	341	100
15	1	1	1	0
30	25	29	106	31
50	16	19	153	45
60	4	5	8	2

80	7	8	19	6
Unknown	33	38	54	16

5.1.2 Individual cyclists characteristics related factors

Table 5 shows that both SBCs and non-SBCs are more common among older cyclists (60+ years) and that the gender distribution is similar. This finding is consistent with the study by Ormel, Klein Wolt, & den Hertog (2008), which reported that over 60% of hospitalized cyclists involved in SBCs were aged 55 and older, and with the study of Wijlhuizen & Bos (2020) the Ambulance and BRON datasets reveal that incidents involving bicycles and motor vehicles are relatively high among older (60+) victims. This suggests that age impacts the types of accidents involving cyclists. Seniors aged 55 and older are more likely to experience accidents due to physical limitations, especially when mounting or dismounting their bikes. They are also more susceptible to being startled or distracted by other road users, leading to SBCs that often result in serious injuries. Moreover, about a quarter of seniors are hospitalized following SBCs (Ormel, Klein Wolt, & den Hertog, 2008).

From the analysis the gender distribution is similar for both SBCs and Non-SBCs. However, this finding contrasts with existing literature, where evidence suggests that male cyclists are more likely than female cyclists to be involved in a bicycle crash (both SBC and Non-SBC) (Prati et al., 2019). These gender differences may be attributed to social and cultural factors that influence variations in mobility patterns, risk perception, attitudes, and engagement in risky behaviors between men and women (Useche et al., 2018).

It is notable that the proportion of unknowns for Non-SBCs is relatively high in this category, which may suggest gaps in data collection or reporting inconsistencies for these types of crashes. This makes it more challenging to draw definitive conclusions about the factors influencing Non-SBCs.

Table 5: Factors related to individual cyclist characteristics

Factors	**SBC**		**Non-SBC**	
	n	(%)	n	(%)
Individual cyclist characteristics				
Age of cyclists	**86**	**100**	**341**	**100**
0-19	5	6	13	4
20-39	4	5	9	3
40-59	14	16	14	4
60+	32	37	23	6
Unknown	31	36	282	83
Gender	**86**	**100**	**341**	**100**
Male	29	34	31	9
Female	26	8	28	8
Unknown	31	36	282	83

5.1.3 Temporal related factors

Table 6 indicates that SBCs are more frequent in the afternoon (14:00 – 18:00), while Non-SBCs tend to occur later in the evening (18:00 – 22:00). According to Ormel, Klein Wolt, & den Hertog (2008) the risk of SBCs is higher at night (between 0:00 and 6:00). In SBCs this may be because the darkness conceals road surface issues or obstacles, making it impossible for cyclists to anticipate or avoid the crash and therefore harder to brace for the impact (Ormel, Klein Wolt, & Den Hertog, 2008). Both types of crashes are more frequent on weekdays. This contrasts with the findings of Ormel, Klein Wolt, & den Hertog (2008) which indicated a higher risk of SBCs on weekends due to increased alcohol consumption during those times. Additionally, Møller et al. (2021) found that cycling under the influence of alcohol is a significant factor in SBCs compared to other types of bicycle accidents. However, the study of *Alluri et al. (2017)* indicates that crashes involving Non-SBCs were more frequent on weekdays. Seasonal trends show SBCs peak in spring, whereas Non SBCs are more frequent in summer. This finding is in line with *Reurings et al. (2012)* where the risk of cyclists being seriously injured in a non-motor vehicle accident is higher in summer than in winter but contrasts with Utriainen (2020) who observed that winter was the most frequent season for SBCs. However, it is possible to speculate that SBCs might be more common in colder countries (e.g., Sweden, Finland, and Norway) than in regions with milder winters and less snow and ice *(Utriainen et al., 2023).* Furthermore, daylight conditions and dry weather are associated with the highest number of crashes in both categories.

Table 6: Temporal related factors

Factors	**SBC**		**Non-SBC**	
	n	(%)	n	(%)
Temporal related factors				
Weather	**86**	**100**	**341**	**100**
Dry	67	78	287	84
Rain	8	9	42	12
Unknown	11	13	12	4
Time of crash	**86**	**100**	**341**	**100**
06:00–10:00	12	14	77	23
10:00–14:00	31	36	72	21
14:00–18:00	28	33	137	40
18:00–22:00	10	12	48	14
22:00–06:00	7	8	5	2
Day of crash	**86**	**100**	**341**	**100**
Weekday	60	70	53	16
Weekend	26	30	26	7
Unknown	0	0	262	77
Season	**86**	**100**	**341**	**100**
Winter	12	14	61	18
Spring	30	35	75	22
Summer	17	20	92	27
Fall	27	31	113	33
Lighting	**86**	**100**	**341**	**100**
Daylight	72	84	259	76
Darkness	9	10	22	22
Twilight	1	1	20	20
Unknown	4	5	40	40

5.2 Spatial autocorrelation

The analysis of Global Moran's I statistics for the two different crash types (SBC and Non-SBC) across the two different datasets (Ambulance and BRON) reveal significant spatial autocorrelation, indicating a clustered spatial distribution, see Table 7.

Table 7: Global Moran's I statistics results

Crash type	**Dataset**	**Moran's Index**	**Z-score**	**P-value**	**Spatial distribution (α = 0.05)**
SBC	Ambulance	0,015	2,318	0,020	Clustered
SBC	BRON	0,064	3,962	0,000	Clustered
Non-SBC	Ambulance	0,024	3,812	0,000	Clustered
Non-SBC	BRON	0,033	2,913	0,003	Clustered

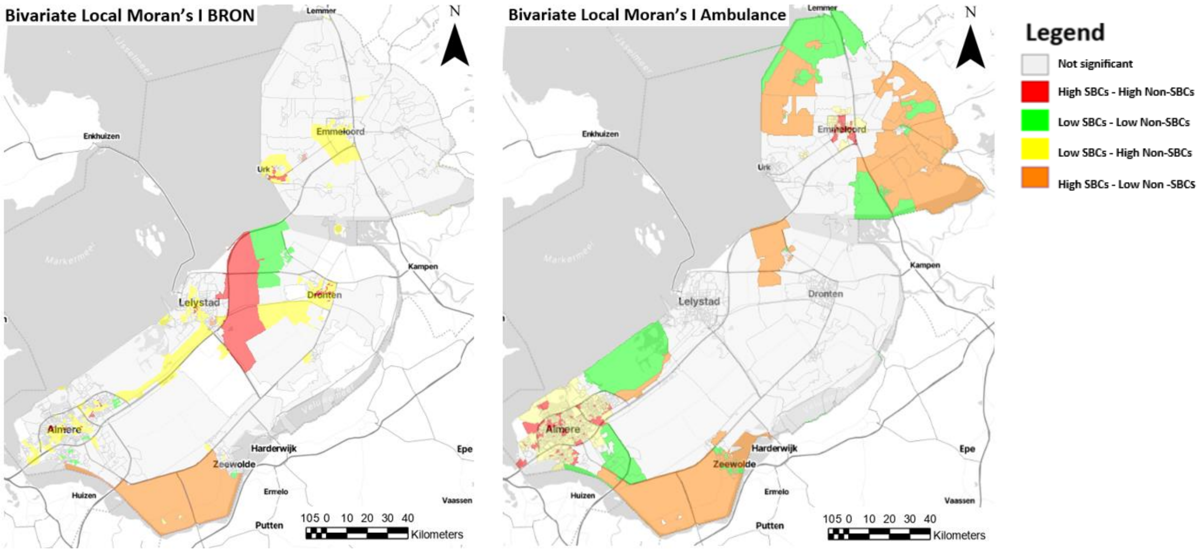


Figure 11: Bivariate Local Moran's I for the BRON and Ambulance datasets.

The significant P-values across all datasets suggest that the crash types analyzed are not randomly distributed but are spatially clustered. This clustering pattern indicates that crashes are influenced by spatial factors and tend to occur in specific areas rather than being evenly dispersed across the study area.

After Global Moran's I was calculated, Local Moran's I was determined for all four combinations (see Appendix II). To establish the threshold distance required for the calculation, Incremental Spatial Autocorrelation (ISA) was conducted. In Appendix III this result can be found. A single peak was identified at 450 meters, which will serve as the threshold distance, as it marks the point where spatially significant clusters start to emerge (Choudhary et al., 2015). The figures (figures can be seen in Appendix II) reveal that HH clusters appear exclusively in Lelystad and Almere, suggesting that these cities experience a high concentration of SBCs and Non-SBCs. HL clusters, in contrast, are more commonly found at the boundaries of municipalities or in rural areas. These clusters exhibit high local crash concentrations but are surrounded by regions with lower crash frequencies. LL clusters are only seen in the Ambulance dataset of Non-SBCs in Almere, representing areas with low crash concentrations both locally and in surrounding areas. Lastly, LH clusters are the most widely distributed, appearing in all the figures. These clusters show areas with low local crash frequencies but are surrounded by regions with higher crash frequencies.

After identifying the local clustering of each crash type in each dataset using Local Moran's I, the next step was to analyze the differences between the crash types within each dataset. Figure 11 display the results of this analysis. The comparison between SBCs and Non-SBCs is illustrated such that the first "High" or "Low" in the legend represents the clusters of SBCs, and the second one represents the clusters of Non-SBCs. The Figure illustrates that in the BRON dataset (left picture), areas with low clusters of SBCs in Almere, Lelystad, Dronten, Urk, and Emmeloord are surrounded by areas with clusters of high Non-SBCs. Although low-low categories are relatively sparse, they are more frequently observed on the outskirts. In contrast, several high-high categories are identified within the urban areas of Almere, Dronten, Lelystad, and Urk, suggesting that both SBCs and Non-SBCs clusters are high in these regions. A noteworthy high-low category is located in Zeewolde, where high SBCs are observed while clusters of Non-SBCs are low in the surrounding area. In the ambulance dataset (right picture) the results present a somewhat different pattern. High of SBCs and low Non-SBCs are more prevalent in the outskirts and non-urban areas of Flevoland. Indicating that SBCs differ from Non-SBCs in terms of their locations. Additionally, all the low-low categories are also found in these areas. Conversely, high-high and low-high categories are observed only in the urban areas of Almere and Emmeloord, indicating that these urban regions experience both high occurrences of clusters of SBCs and clusters of Non-SBCs, as well as having low SBCs clusters with high Non-SBCs clusters in the neighborhood.

Overall, these results show that urban areas experience a high cluster of SBCs and Non-SBCs, with Non-SBCs being particularly prevalent. This finding aligns with previous research, who also observed a higher incidence of crashes in urban areas compared to non-urban areas (Siddiqui et al., 2014). Additionally, the results suggest that cluster of SBCs are more commonly found in the non-urban areas of Flevoland with no clusters of Non-SBCs surrounding it, indicating a different spatial distribution compared to Non-SBCs.

5.3 Spatial analysis

The analysis before started with a spatial autocorrelation to identify spatial relationships for and between SBCs and Non-SBCs by investigating it on PC5 level. However, examining road segments will provide more detailed information about which specific roads are particularly dangerous. Therefore, the NKDE was used. NKDE is a method that estimates the density of events along network data like roads and was applied to analyze crash clustering. As a result density maps were created. Additionally, the DRD parameter was used to compare these crash densities between SBCs and Non-SBCs.

In Figure 12 the result of the DRD can be seen for the municipality Almere (the rest of the analysis can be found in Appendix IV). Here, the pink road segments indicate that the normalized crash density is higher for SBCs compared to Non-SBCs, while the blue road segments indicate that the normalized crash density is lower for SBCs compared to Non-SBCs. In other words, the density of SBCs is higher on the pink segments, while on the blue segments, the density of SBCs is lower than that of Non-SBCs.

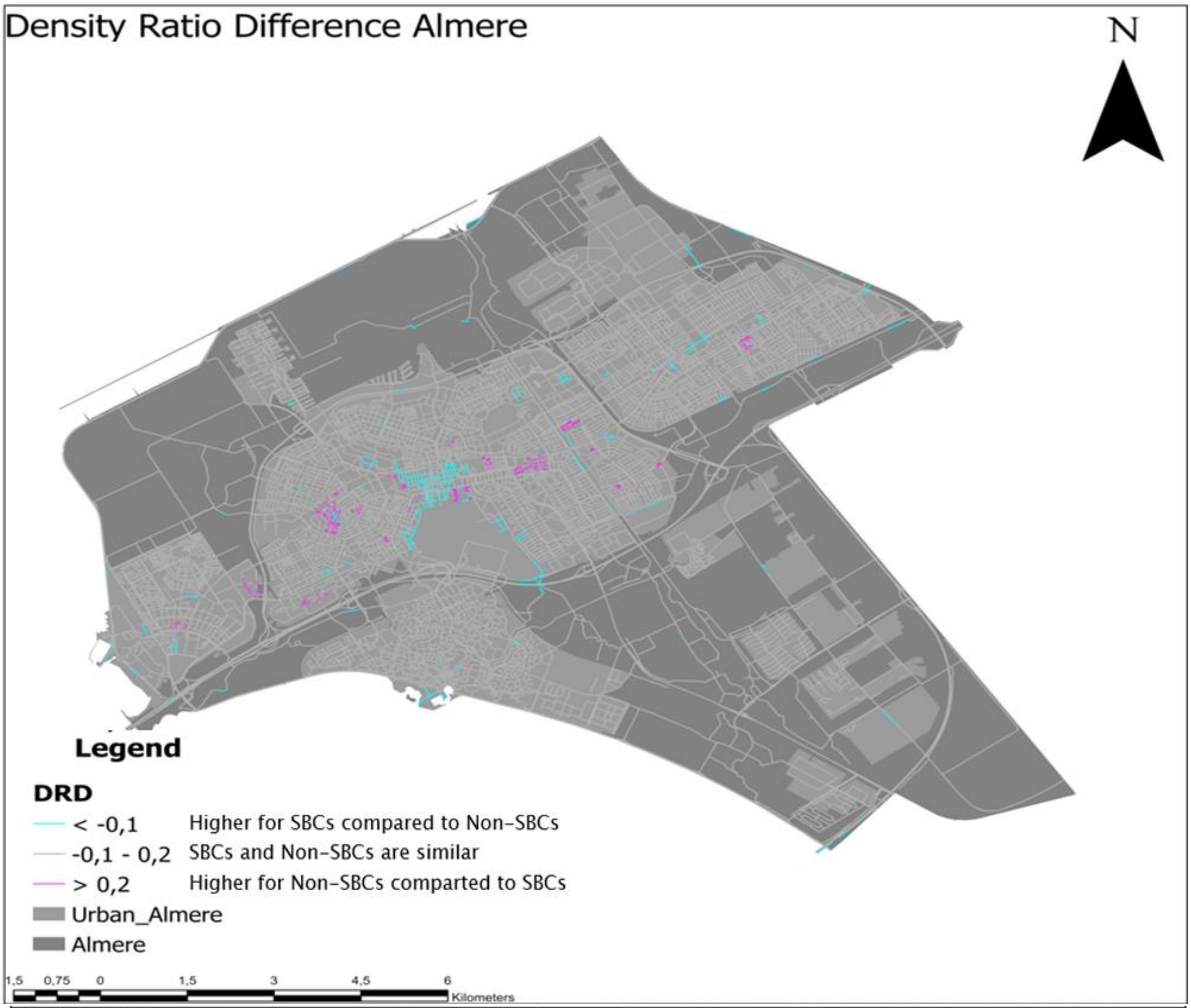
From Figure 12 there can be seen that most crashes are located in the urban areas of Almere. Furthermore, there can be observed that the roads tend to cluster. Especially, the middle section is blue, with the help of Google Maps there can be seen that this area is also the city center of Almere, where lots of shops, restaurants and even the hospital is located. The same conclusion holds for the cities Urk, Dronten, Noordoostpolder and Zeewolde. Indicating that a significant number of Non-SBCs occur within urban areas, particularly in city centers. This can be due to a higher concentration of people and vehicle movement. This finding aligns with studies as the one from Abdel-Aty & Radwan (2000), which concluded that urban roadway segments pose a higher crash risk compared to rural sections. Additionally, research by Loidl et al. (2016) emphasizes that crash risks tend to be elevated in city centers due to the complex interaction of various road users, increased traffic volumes, and the presence of multiple transport modes. However the study of Schepers et al. (2015b) suggest that well-designed cycling infrastructure in dense urban areas can mitigate some of these risks.

Additionally, there are two clusters of pink road segments located in Almere. These clusters are notable compared to other cities, where the pink road segments are more uniformly dispersed. In Almere, the pink clusters are distinctly located near train stations, grocery stores, and several schools. This high density of SBCs could be due to increased bicycle traffic in these streets, as SBCs can occur from interactions with other road users as cyclists might fall while swerving or braking to avoid another vehicle, lose sight of obstacles because of a vehicle in front of them, or be distracted by the behavior of someone behind them (Davidse et al., 2014).

However, when looking at the results of the bivariate Local Moran's I, clusters of SBCs primarily appear in non-urban areas, but in this road segment-based analysis, such clusters are not evident. One reason for this can be that analyzing crashes at the road segment level offers a more detailed view, while the PC5 level, which covers larger areas, may miss important details and variations specific to smaller locations (Yang & Loo, 2016).

Furthermore, a legend was employed to represent the density ratio difference, with blue indicating values less than -0.1, pink for values greater than or equal to 0.2, and grey for values in between. This approach was also

chosen because it highlights the extremes—representing the top and bottom 20% of density ratios—while simplifying the interpretation of density ratio differences across various road segments and maintaining consistency throughout the study. Although this legend, based on data from Almere, may not capture variations as effectively in other cities or clearly indicate SBCs on road segments in non-urban areas, it allows for a clear visual distinction between segments with different variations in density ratios.



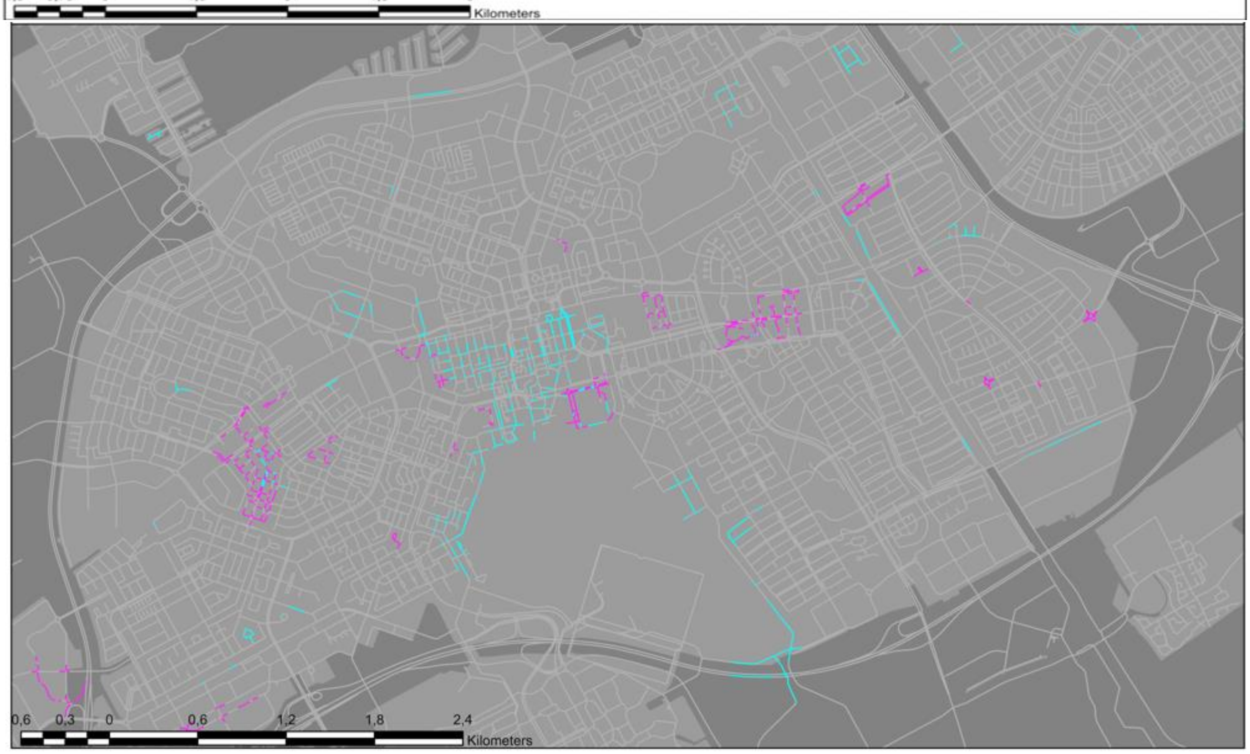


Figure 12: Density Ratio Difference Almere

5.4 Statistical analysis

The NBR model was used to analyze the factors influencing both SBCs and Non-SBCs at the road segment level. For both, the analysis included explanatory variables such as BKMT, urban area, educational facilities, train stations, population density, land-use variables (MXI and office density) and highstreets. The results are shown in Table 7 which present the regression coefficients (β), standard errors (SE), and the p-value of parameters. Additionally, the table highlights the overall goodness-of-fit measures, namely the log-likelihood values and Akaike Information Criterion (AIC) scores, which help compare the model fit for SBCs and Non-SBCs. Lower AIC values, combined with higher log-likelihood values, indicate a more effective model in explaining the observed variability in crash counts. The theta values further highlight differences in overdispersion between SBCs and Non-SBCs, revealing differences in variability between the two crash types. The analysis shows that SBCs have less variability and are better predicted by the model, as indicated by a lower AIC and higher theta value. In contrast, Non-SBCs exhibit greater overdispersion.

Figure 13 shows the "standardized coefficients" (Siegel, 2016) for the significant variables. Standardized coefficients were selected because they are independent of scale and units, which makes them more effective than regular coefficients for comparing the direction and magnitude of effects (Zhao et al., 2021).

5.4.1 BKMT

The result of BKMT on the frequency of SBCs and Non-SBCs is shown in Figure 13. The figure reveals that BKMT (bike kilometers traveled) significantly impacts crash counts for both SBCs and Non-SBCs. Specifically, the results show a negative correlation between the total kilometers traveled by cyclists and the number of crashes ($P<0.05$). This finding indicates that more kilometers traveled are associated with fewer crashes. This result aligns with Schepers (2012), which observed that increased bicycle use per kilometer traveled is linked to a reduced risk of experiencing an SBC. However, for the Non-SBCs the relationship between BKMT and crash frequency remains complex and not fully understood. While some studies suggest that a higher number of bicyclists on the road (and thus more kilometers traveled) can enhance safety (Jacobsen, 2015; Vandenbulcke et al., 2009), other research indicates a link between greater bicycle volumes and an increase in crashes and fatalities (Wegman et al., 2012).

Since the dataset (see Figure 9) indicates that most road segments have low bicycle intensity, the low frequency of crashes on these roads segments might reflect a smaller number of interactions, thus fewer opportunities for crashes. This could explain why increased bicycle kilometers travelled is associated with fewer crashes. However, in SBCs and Non-SBCs, crashes are not solely caused by interactions.

Another explanation for this is the inclusion of other variables in the model, such as population volume, which is capturing much of the effect that would have otherwise been attributed to the BKMT.

5.4.2 Cycling infrastructure

The result reveals that both SBCs and Non-SBCs are more likely to occur on roads with bicycle lanes marked on the carriageway compared to roads with mixed traffic conditions. This finding is statistically significant ($P < 0{,}05$), indicating that marked bicycle lanes increase the likelihood of crashes for both SBCs and Non-SBCs when compared to roads with mixed traffic conditions. This finding is consistent with the result of Welleman & Dijkstra (1988), who, after adjusting for exposure, concluded that bicycle lanes are riskier than both separated bicycle tracks and mixed traffic conditions. However, some studies suggest that bicycle safety has improved on roads with bicycle lanes (DiGioia et al., 2017a; Pulugurtha & Thakur, 2015), while others found no significant safety advantages over roads with mixed traffic conditions (Petegem et al., 2021).

Furthermore, no statistically significant results were found for separated bicycle lanes in this study. Nevertheless, previous research has shown that separated bicycle lanes are generally the safest option for cyclists (Petegem et al., 2021; Wang et al., 2019).

5.4.3 Urban

The results indicate that road segment in urban areas do not significantly affect the frequency of SBCs or Non-SBCs. For both types of crashes, the association with urban areas is weak and not statistically significant, suggesting that road segments within a urban area do not impact crash frequencies in this study. This result was unexpected, as the DRD analysis revealed a high density of crashes occurring in urban areas for both crash types.

5.4.4 Highstreet

The highstreet variable demonstrates a statistically significant relationship with the frequency of Non-SBCs but not for SBCs. This is an interesting finding, as it may suggest that Non-SBCs occur more frequently in areas with a higher concentrations of shops, meeting places, offices, industries, accommodations, healthcare facilities, and sports centers. These locations typically experience heavier traffic, both motorized and non-motorized, which could increase the likelihood of interactions between bicycles and other road users, leading to a higher occurrence of Non-SBCs in these areas. Additionally, since SBCs are often associated with roads that have lower speed limits and traffic volumes, it follows logically that higher traffic areas would see more incidents involving non-SBCs.

5.4.5 Proximity to educational facilities and train stations

No significant relationship between proximity to railway stations and educational facilities and the frequency of SBCs and Non-SBCs was found in this study. This result is consistent with the findings of the study of Uijtdewilligen et al. (2023), which also reported no significant relationship. This indicates that road segments within 150 meters of these destinations do not have any impact on the frequency of SBCs and Non-SBCs. However, it is important to note that this does not necessarily mean that areas around these facilities are safer for cyclists.

5.4.6 Population density

Population density is a significant predictor having a significant effect on both the frequency of SBCs and Non-SBCs. This is likely due to the higher volume of traffic and interactions between cyclists and other road users in densely populated regions. As according to Reurings et al. (2012) 21% of SBCs are caused (in part) by the behavior of someone else. This is the case, for example, in an crash where someone has to swerve to avoid an opening car door and falls due to this evasive maneuver. However, it should be noted that SBCs involve more contributing factors beyond just bicycle interactions.

Table 7: Results of NBR of SBCs and Non-SBCs

Explantory variables	SBCs			Non-SBCs		
	β	SE	Pr(>|z|)	β	SE	Pr(>|z|)
(Intercept)	-3,39	0,16	<2e-16***	-3,15	0,15	<2e-16***
BKMT	-0,03	0,16	0,04*	-0,04	0,01	0,00**
Bicycle lanes marked on the carriageway (reference category: mixed traffic conditions)	0,27	0,02	0,04*	0,29	0,13	0,02*
Seperated bicycle tracks (reference category: mixed traffic conditions)	0,07	0,13	0,49	0,04	0,10	0,71
Urban	0,03	0,10	0,83	0,02	0,15	0,87
Highstreet	0,05	0,16	0,71	0,22	0,12	0,06.
Educational Facilities	3,80E-03	0,12	0,97	-0,06	0,10	0,56
Trainstation	-1,18	0,10	0,24	1,44	1,03	0,16
Population Density	0,01	1,01	<2e-16***	0,01	4,71E-04	<2e-16***
MXI	2,24E-03	3,13E-04	8,26E-13***	2,90E-03	3,90E-04	0,00***
Office Density	6,33E-04	1,44E-04	1,12E-05***	9,06E-04	1,54E-04	3,83-09***
AIC	7953,50			9679,90		
2 x log-likelihood	-7929,47			-9655,90		
Theta	1.061			0.3162		
Null deviance	5731.4 on 19.617 degrees of freedo m			5774.9 on 19617 degrees of freedom		
Residual deviance	5014.3 on 19.607 degrees of freedo m			4846.2 on 19607 degrees of freedom		

*Signifiant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

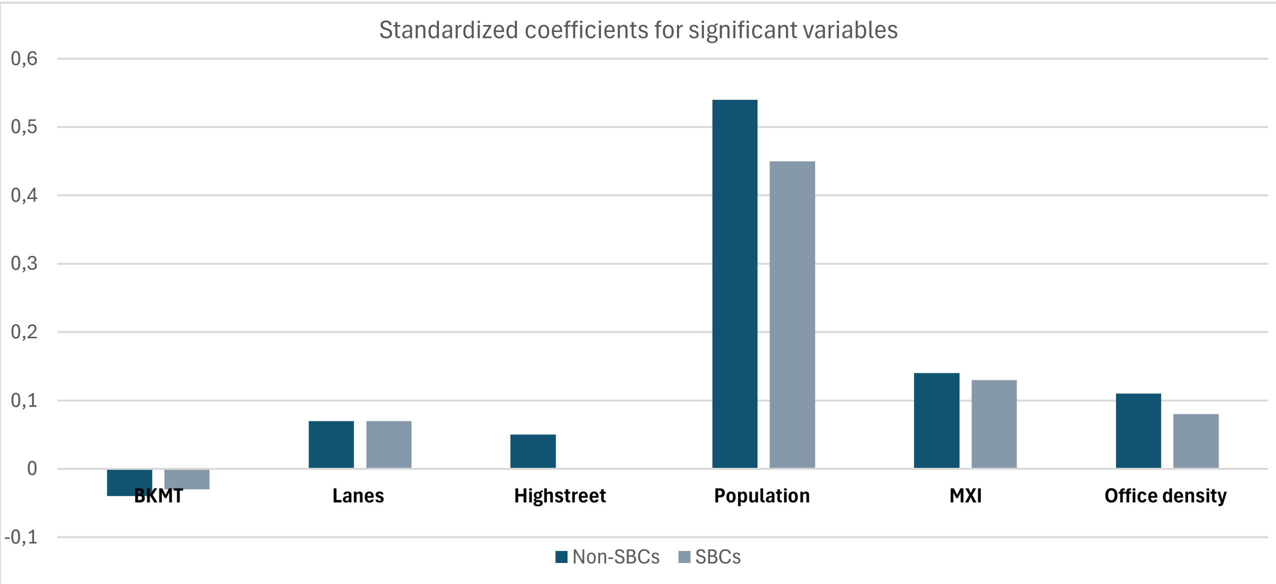


Figure 13: Standardized coefficients for significant variables, Lanes = Bicycle lanes marked on the carriageway

5.4.7 Land-use variables

Areas with a lot of offices have higher crash frequencies for both SBCs and Non-SBCs. This suggests that road segments with office areas increase the likelihood of SBCs and Non-SBCs. The same result holds for MXI. Previous studies on bicycle crash frequency have scarcely investigated MXI. However, the study of Chen (2015) suggests that a 1.0% increase in MXI is associated with a 0.62% rise in the number of bicycle crashes. This positive correlation may be due to conflicts between concentrated human activities in areas with diverse land use purposes (Chen, 2015).

5.5 Limitations and future directions

Several limitations in the data processing and modeling may have influenced the results of this study. One issue involves the quality of the spatial joins used to link crash data to road segments. Specifically, the ambulance data presents a challenge because it does not represent the exact location of the crash but rather the location where the ambulance arrived. This introduces a potential source of uncertainty, as crashes may have been assigned to incorrect road segments. This misalignment could lead to errors in estimating crash frequencies on specific roads, particularly in dense urban areas where spatial precision is critical.

Additionally, while efforts were made to account for important variables such as population volume and traffic-related factors, there remains the possibility that unmeasured or unobserved factors influenced the model outcomes. The inclusion of certain variables may have also introduced complexities in interpreting the effects of others, as observed with the negative coefficient for the BKMT variable. The weak correlation between BKMT and population volume suggests that the effects of BKMT may be influenced by other factors that are not fully captured in the model.

The decision to use a NBR was made to address overdispersion in the count data, yet alternative modeling approaches, such as zero-inflated models, may offer different insights into the nature of the crashes, particularly for rare or infrequent events. Future studies could explore these alternatives to provide a more robust understanding of crash risks.

The data processing methods and approaches used in this study can be applied to traffic crash analysis in other cities. However, since the findings are based on data from the Netherlands, they may not be directly applicable to other regions, like urban areas in the United States. This is mainly due to differences in land use and road infrastructure, especially in the design and availability of cycling paths. These differences also affect travel behavior and travel and cycling volumes, making it hard to generalize the results to other areas (Asadi et al., 2022).

Another limitation of this study is the underreported crashes in the datasets, which is a common issue of police records. SBCs are often missed because they might only involve ambulance responses or cyclists seeking care themselves. Also police often do not handle or record many crashes, like SBCs, because there is no liability involved Wijlhuizen & Bos (2020). Consequently, only severe crashes and those involving motor vehicles are usually reported, leading to an incomplete picture of SBCs and potentially affecting the study's results.

Moreover, while the bicycle intensity data is certainly useful for policy applications, research, and reports, it is important to remember that it represents an allocation of the annual average weekday bicycle mobility based on a traffic model. Therefore, this model may either underestimate or overestimate bicycle usage on certain roads, potentially introducing bias into the results.

6. Discussion

The results of this study contribute to an understanding of the relationship between BE factors, SBCs and Non-SBCs. The negative relationship between BKMT and crash frequency aligns with the "safety in numbers" phenomenon, where higher bicycle volumes lead to greater visibility and caution from other road users, thus reducing crashes. This finding, supported by Schepers (2012) and Jacobsen (2015), suggests that increasing cycling levels could enhance safety by fostering more predictable and safer interactions between cyclists and other road users. However, this effect appears to be less straightforward for Non-SBCs, where interactions with motor vehicles, pedestrians, and other cyclists are more frequent. In areas with higher population density and traffic intensity, such as highstreets, Non-SBCs are more likely to occur, as shown by the significant positive result in this study. These findings align with the conclusions of Wegman et al. (2012), who noted that dense urban areas, characterized by high traffic volumes and multiple road users, tend to see more crashes due to a higher probability of conflicts.

This study observed that the cycling infrastructure, such as bicycle lanes marked on the carriageway, increased the likelihood of both SBCs and Non-SBCs. This contradicts some studies, such as DiGioia et al. (2017), which suggest that marked bicycle lanes improve safety. The difference may be explained by varying road user behavior and traffic conditions.

The lack of statistical significance for urban area in predicting SBC and Non-SBC occurrences was unexpected, especially since the DRD analysis showed that urban areas had higher crash densities. This may suggest that other factors, such as traffic volumes or specific road features, are stronger determinants of crash frequency in urban settings, rather than the urban designation itself. In terms of population density, the significant positive relationship observed is consistent with past studies (Ding et al., 2020; Siddiqui et al., 2012) that found higher crash rates in densely populated areas due to increased interactions between cyclists and other road users.

Lastly, the results showed no significant relationship between proximity to educational facilities and train stations and crash frequencies. While Uijtdewilligen et al. (2023) also found no clear link between these factors and crash frequency, it is possible that the effect of these destinations is more nuanced. For example, certain times of the day or specific age groups, like children or the elderly, may be more affected by these environments. The lack of significance in this study suggests that proximity alone may not be a strong predictor, but other contextual factors, such as timing of the day and age and gender of road users could play a more important role.

7. Conclusions

In conclusion, this study aimed to answer the main question: "What built environment factors contribute to SBCs and how do they compare to those affecting Non-SBCs?" To address this, the study explored several sub-questions:

1) *What information is available in the BRON and ambulance datasets for SBCs and Non-SBCs, and how do the datasets and the crash types compare?*

The descriptive analysis of the BRON and Ambulance datasets reveal differences in the frequency and distribution of SBCs and Non-SBCs across Flevoland. Both datasets indicate higher crash frequencies in urban municipalities such as Almere and Lelystad. Specifically, the Ambulance dataset reveals that Almere has the highest rate of SBCs per 100,000 inhabitants, while Lelystad has the highest rate of Non-SBCs. However, the

BRON dataset shows that Urk and Noordoostpolder have the highest number of bicycle crashes per 100,000 inhabitants. These findings suggest that while the ambulance dataset is indicating that urban areas tend to report higher crash frequencies, the BRON dataset indicates that more non-rural municipalities like Urk and Noordoostpolder are experiencing more crashes. This indicates that there are differences between the Ambulance and BRON datasets in terms of the spatial distribution and frequency of reported crashes for both crash types.

The descriptive analysis of the BRON dataset reveals that SBCs are associated with older cyclists and are more common on rural roads and straight road segments, whereas Non-SBCs are more frequent in urban environments and at intersections. Temporal factors also differ, with SBCs peaking in the afternoon and being more prevalent in spring, whereas Non-SBCs are more common in the evening and summer months. Additionally, SBCs are generally occurring on lower-speed roads, while Non-SBCs are more occurring with higher-speed limits.

2) *What are the spatial patterns of SBCs, and how do these patterns differ from those of Non-SBCs?*

The Global Moran's I statistics reveals significant spatial clustering for both SBCs and Non-SBCs in the Ambulance and BRON datasets, indicating that crashes are not randomly distributed but concentrated in specific areas. Local Moran's I analysis identifies key patterns: urban areas like Lelystad and Almere show high-high clusters, where both crash types are frequent. Moreover, the Bivariate Local Moran's I analysis concluded that rural and border regions display high-low clusters, indicating high clusters of SBCs that are surrounded by low clusters of Non-SBCs. Lastly, The DRD analysis confirms that urban city centers have higher crash densities, consistent with the findings of the Local Moran's I. These results indicate that while urban areas have higher crash frequencies for both SBCs and Non-SBCs, clusters of SBCs are more common in non-urban areas.

3) What is the relationship between built environment factors and the occurrence of SBCs, and how do these relationships differ from Non-SBCs?

This study investigated the relationship between contributing factors and the occurrence of SBCs versus Non-SBCs using NBR. The analysis included the variables BKMT, cycling infrastructure, urban area, land-use variables (including MXI, offices, and highstreets), population density, and proximity to educational facilities and train stations. The analysis shows that higher bicycle kilometers traveled (BKMT) is associated with fewer crashes, reflecting a positive safety effect of increased cycling. However, the relationship with BKMT for Non-SBCs remains complex and not fully understood. The presence of bicycle lanes marked on the carriageway was linked to higher crash likelihoods, aligning with findings that these lanes may increase crash risks compared to mixed traffic conditions, though separated bicycle lanes did not show significant results. Urban areas did not significantly affect crash frequencies in this study. Highstreets, with their concentration of commercial and public facilities, were associated with more Non-SBCs, likely due to increased traffic interactions. Proximity to educational facilities and train stations did not significantly impact crash frequencies. Population density was a significant predictor of both crash types, indicating that higher traffic volumes in densely populated areas contribute to increased crash frequencies. Lastly, the study found that higher office density is linked to increased crash frequencies. This indicates that areas with a high concentration of offices may experience more crashes. Additionally, land-use variables such as mixed-use areas, where diverse activities are concentrated, are associated with higher crash frequencies. This suggests that the presence of multiple types of activities on a road segment could contribute to higher crash frequencies.

In short, this study explored how built environment factors influence SBCs and Non-SBCs, indicating the key findings:

- **Dataset Comparison**: The Ambulance dataset shows higher crash frequencies in urban areas (Almere and Lelystad), while the BRON dataset reveals higher rates in less urban municipalities (Urk, Noordoostpolder). This suggests variations in reporting and crash distribution across the different datasets.
- **Spatial Patterns:** Both SBCs and Non-SBCs experience significant spatial clustering. Urban areas, such as Lelystad and Almere, show high concentrations of both crash types. In contrast, High clusters of SBCs are more prevalent in rural areas with low Non-SBCs clusters next to it.
- **Built Environment Factors:** The MXI, population density, and office density are linked to higher crash frequencies for both SBCs and Non-SBCs. Furthermore, bicycle lanes on carriageways, compared to roads with mixed traffic, are also associated with increased crash frequencies for both types of crashes.

Appendix I: Methodology Global Moran's I and Local Moran's I

Spatial autocorrelation assesses how the presence of one feature is impacted by similar features nearby, offering insights into spatial patterns. Global Moran's I is a method used to analyse if there's a connection between the values of a certain attribute in one place and those in nearby places. It does this by comparing the attribute values using a map-like grid called a spatial contiguity matrix. This method looks at how the attribute values change as you move from one place to another (Gedamu et al., 2024). To calculate the Global Moran's I, the "Spatial Autocorrelation (Global Moran's I)" tool within ArcGIS Pro was used. The equations below are the formulas used to calculate this.

$$I = \frac{\mathrm{n}\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y[i]-\bar{y})(y[j]-\bar{y})}{\sum_{i\neq j}^{n}\sum_{j=1}^{n} W_{ij})(\sum_{i=1}^{n}(y[i]-\bar{y})^2} \quad (1)$$

$$Z\ (I) = \frac{I-E(I)}{S(I)} \quad (2)$$

Where,
N = the total number of crashes (SBCs or NSBCs),
y[i] = a crash occurring at a specific location 'i',
y[j] = a crash occurring at a different location 'j',
$\bar{y}$ = average value of the variable, which in this case, is the mean number of crashes,
W_{ij} = represents the weight assigned to the comparison between crashes at locations 'i' and 'j',
E(I) = expected value of I,
S(I) = standard deviation of I,
Moran's I index ranges from -1 to +1, where larger positive values indicate that similar features are closely clustered, negative values suggest dispersion, and zero signifies randomness in distribution. Typically, Moran's I is converted into a Z score using equation (2), where positive scores indicate similar nearby values and negative scores indicate dissimilar nearby values (Siddiqui et al., 2014). Within this tool, the null hypothesis suggest that there is no spatial clustering of values (Prasannakumar et al., 2011).
Global Moran's I was calculated using a network spatial weight matrix file created in ARCGIS Pro. This file (.swm), generated with the "generate network spatial weight" toolbox, quantified the spatial relationship between crash points in the dataset, considering the network. Using real-world travel networks like roads is more appropriate for accident analysis (ESRI, 2024c). Moreover, Ermagun & Levinson (2018) noted that the network weight matrix offers a clearer connection between links. Thus, the "generate network spatial weights" tool was utilized to model and store spatial relationships between point features restricted to a network dataset.
After the Global Moran's I the Local Moran's I was employed to identify areas of local clustering. This analysis was conducted using the "Cluster and Outlier Analysis (Anselin Local Moran's I)" tool within ArcGIS Pro. The results were visualized on a Local Indicators of Spatial Autocorrelation (LISA) maps, highlighting four types of cluster zones: High-High (HH), High-Low (HL), Low-High (LH), and Low-Low (LL) (Erdogan, 2009). If the value of I is positive, it suggests that the feature is surrounded by similar features (HH and LL), indicating it is part of a cluster. Conversely, a negative value of I indicates that the feature is surrounded by dissimilar features (HL and LH), classifying it as an outlier (Zandi et al., 2023). The formula for local Moran's I is provided in Equation 3.

$$I_i = \frac{X_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq 1}^{N} W_{ij}\,(x_j - \bar{X}) \quad (3)$$

Where,
X_i = a crash occurring at a specific location 'i',
$\bar{X}$ = average value of the variable, which in this case, is the mean number of crashes,
S_i = total of weights,
N = the total number of crashes (SBCs or NSBCs),
W_{ij} = represents the weight assigned to the comparison between crashes at locations 'i' and 'j'.
The Local Moran's I tool in ArcGIS Pro needs input point features to have a defined count, rate, or measurement (ESRI, 2024b). Since this research treats all types of crashes equally, the individual points don't have specific rankings. Therefore, crash counts were aggregated at the PC5 level to create variation in the input values. Like the Global Moran's I the Local Moran's I needed a threshold distance and a conceptualization of spatial relationships between features needed to be specified.
Due to Local Moran's I not accommodating point features on a network in this research, the use of the spatial weights network matrices to conceptualize spatial relationships could not be used. To determine the optimal threshold value, the "Incremental Spatial Autocorrelation" tool in ArcGIS Pro was used. This tool computes Global Moran's I at various distances and corresponding z-scores, with the distance yielding the highest z-score chosen as the optimal threshold distance for further analysis (Hazaymeh et al., 2022). The distance found using this approach is suggested to be used for the spatial autocorrelation analysis with a fixed distance band (ESRI, 2024a).
Initially, the polygon features' distance was too large, preventing a peak from forming. To address this, the Incremental Spatial Autocorrelation tool was executed while excluding all spatial outliers. These spatial outliers were identified by visualizing polygon areas using a Standard Deviation rendering scheme. Polygons with areas exceeding three standard deviations were spatial outliers and were consequently omitted from the initial analysis. Then a peak distance with the outliers removed was identified, this distance was applied universally to all features, inclusive of spatial outliers, ensuring each feature maintained connectivity with at least one or two neighbors (ESRI, 2024a).

Appendix II: Local Moran'I Results

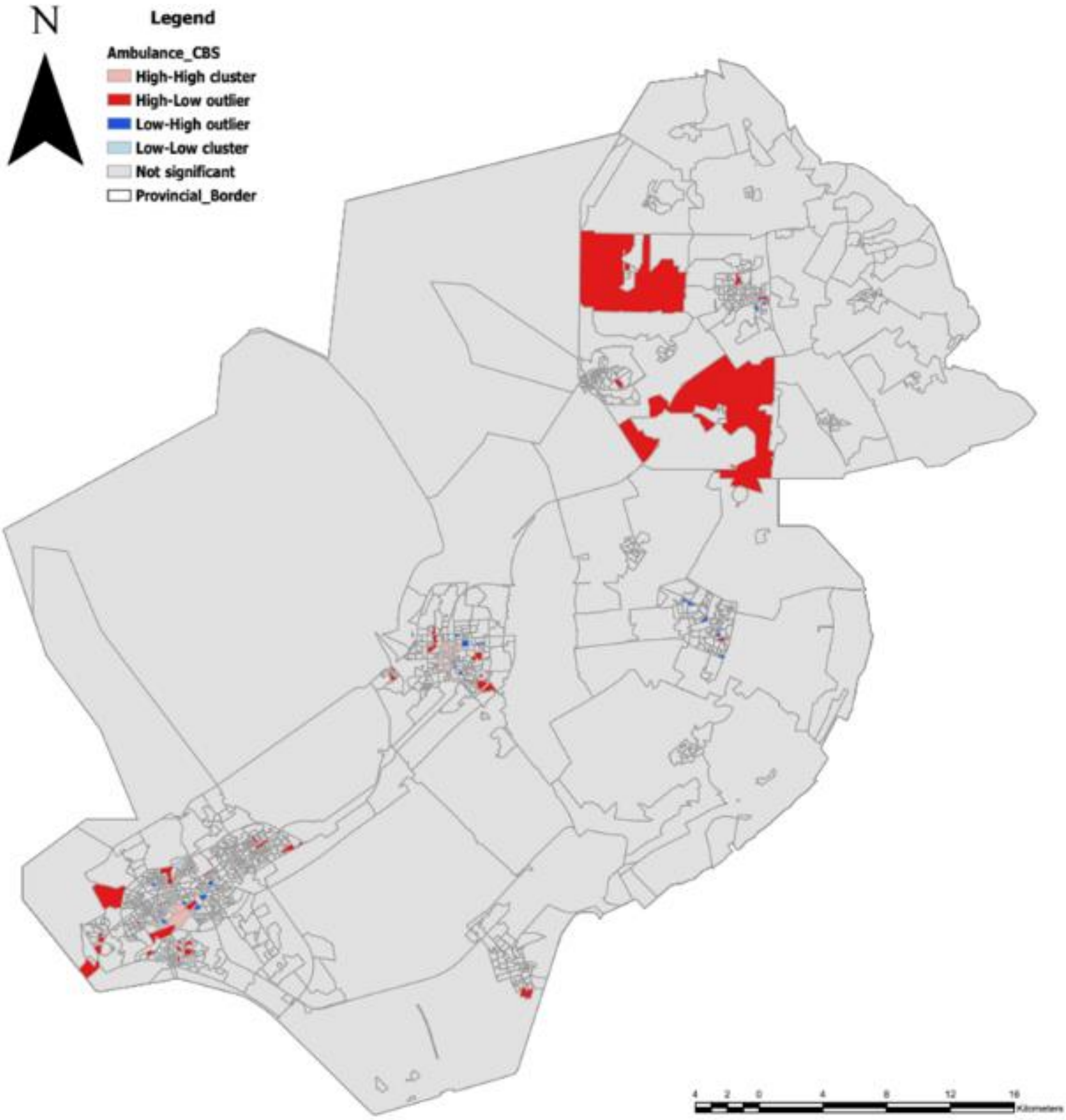


Figure A 1: Ambulance SBCs Local Moran's I

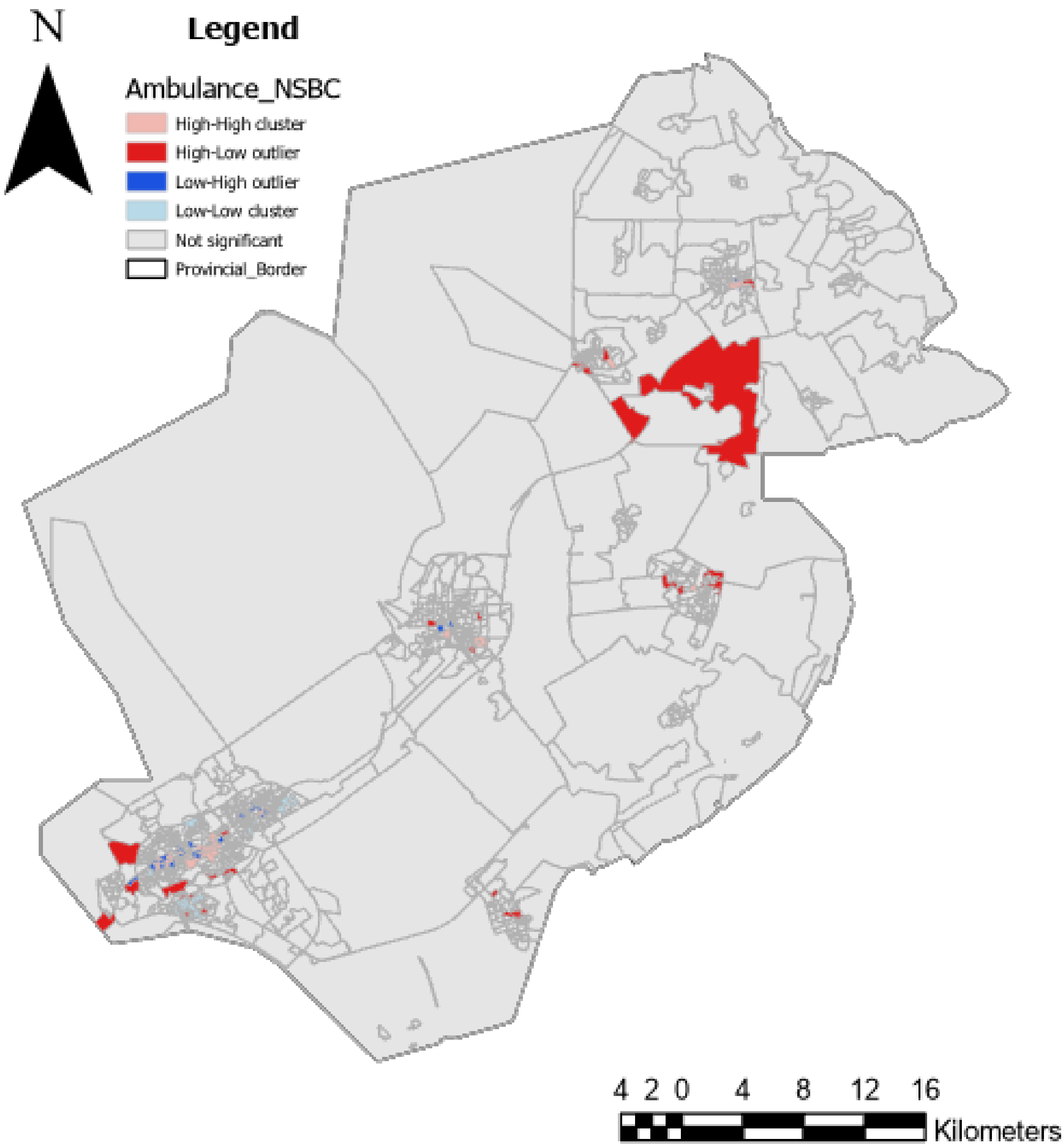


Figure A 2: Ambulance Non-SBCs Local Moran's I

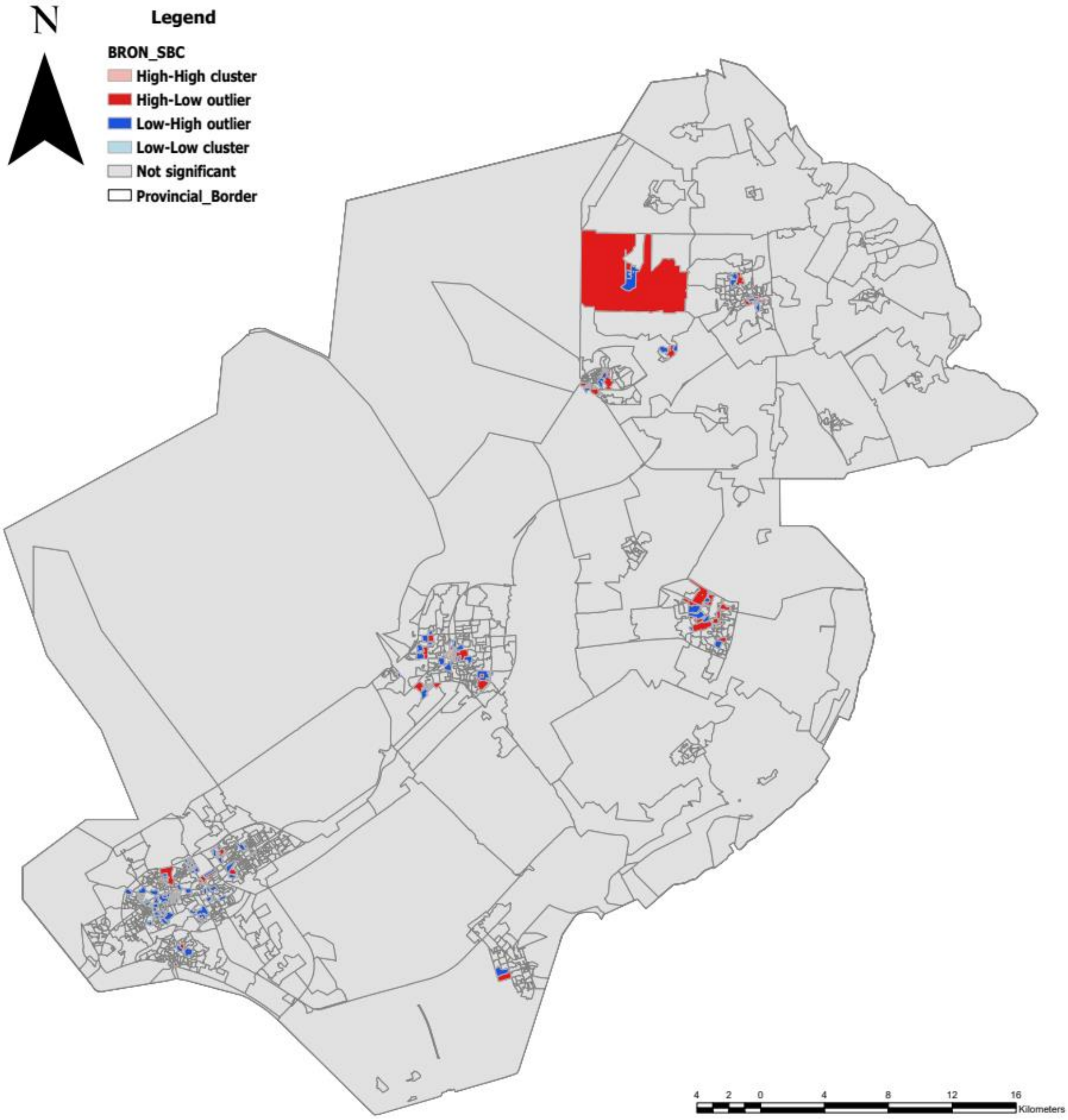


Figure A 3: BRON SBCs Local Moran's I

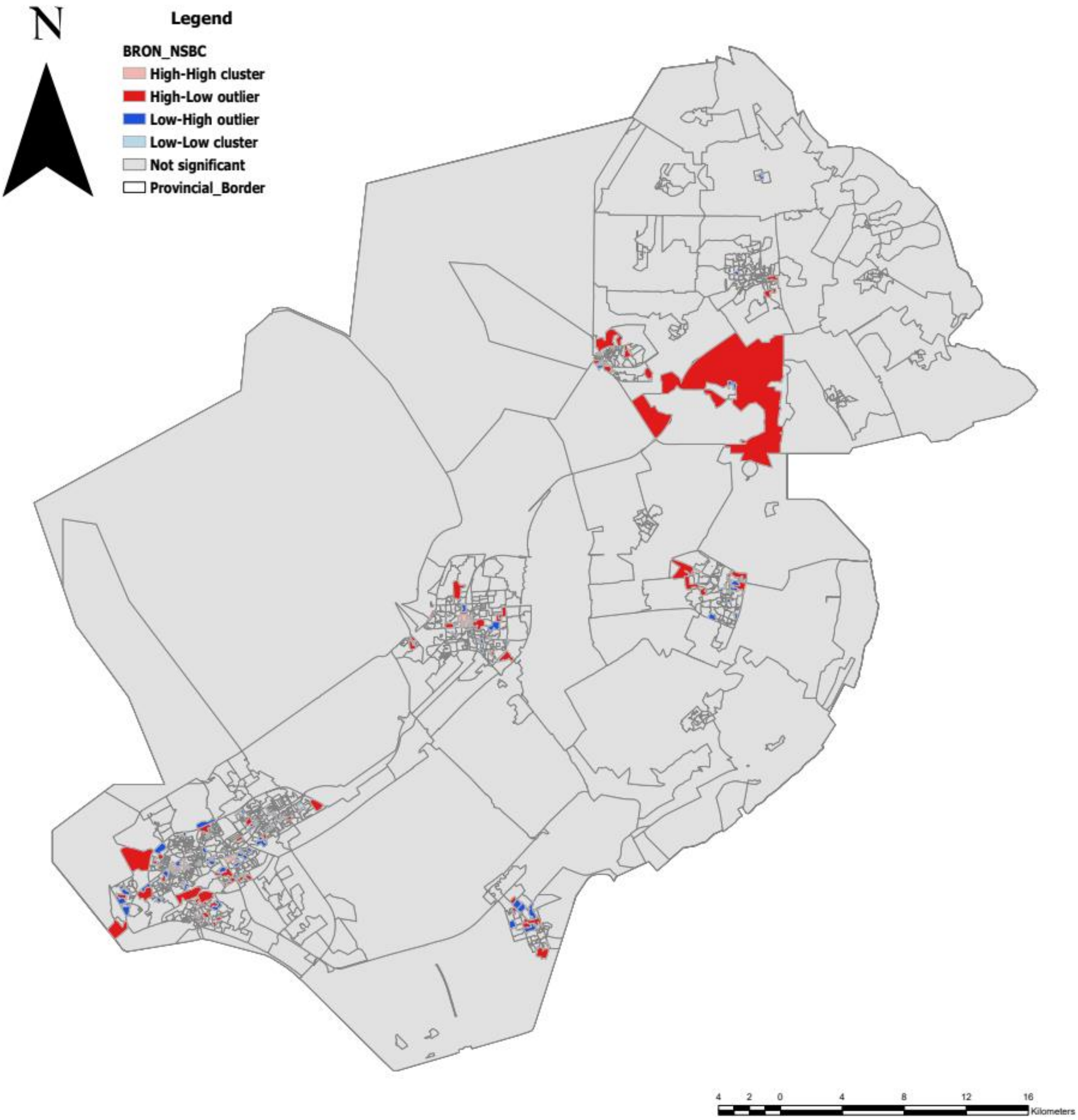


Figure A 4: BRON Non-SBCs Local Moran's I

Appendix III: Spatial autocorrelation by Distance

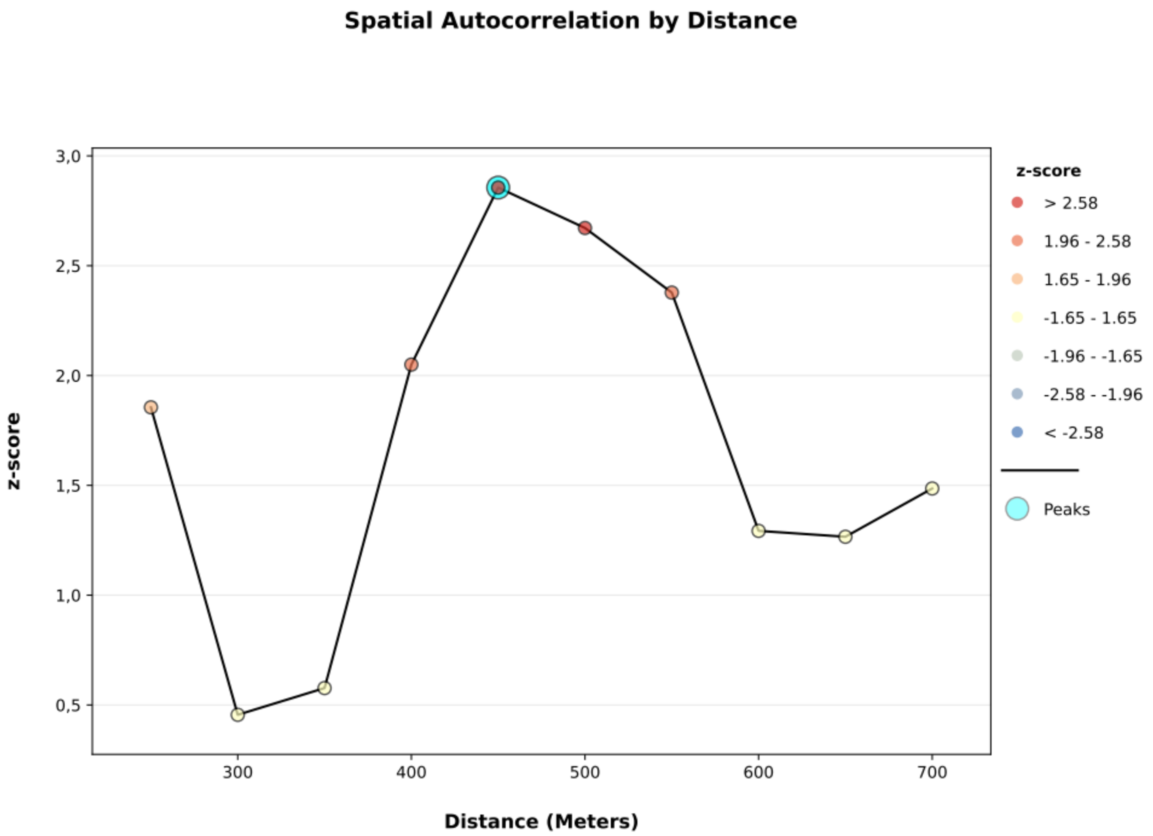


Figure A 5: Spatial autocorrelation by distance

Appendix IV: Density Ratio Difference

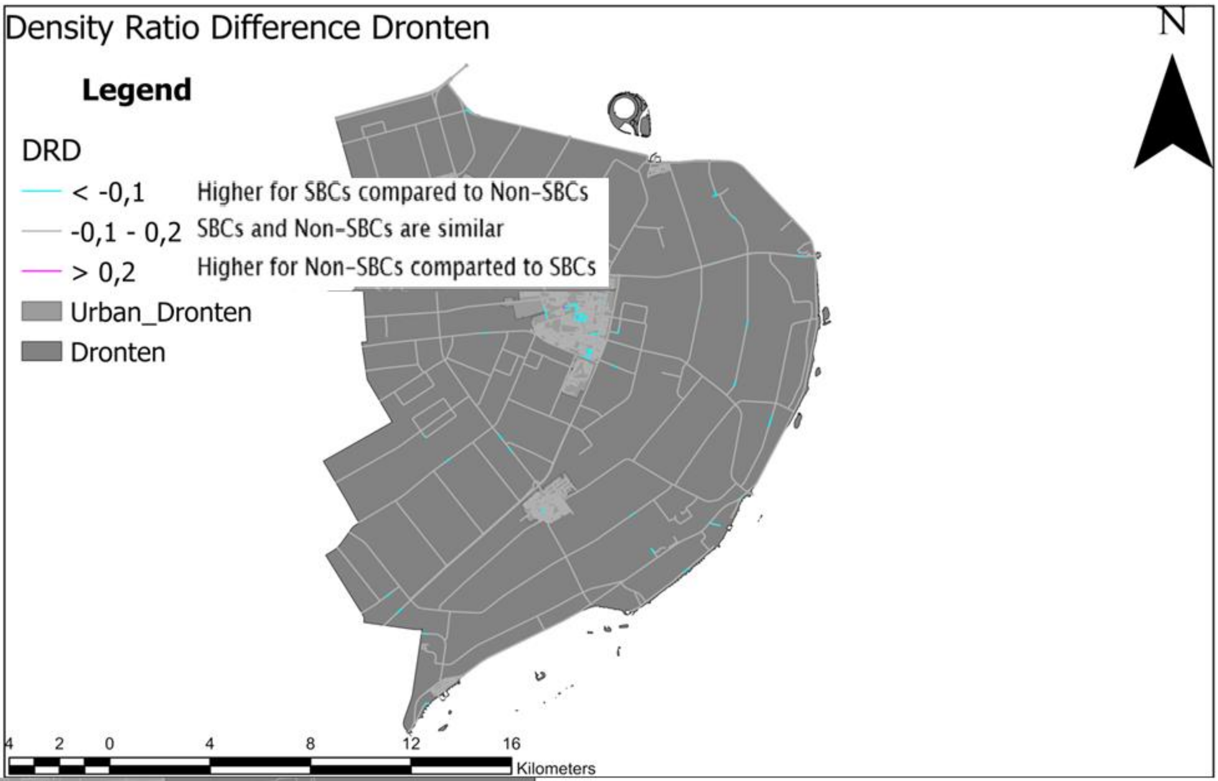


Figure A 6: Density Ratio Difference Dronten

Figure A 7: Density Ratio Difference Lelystad

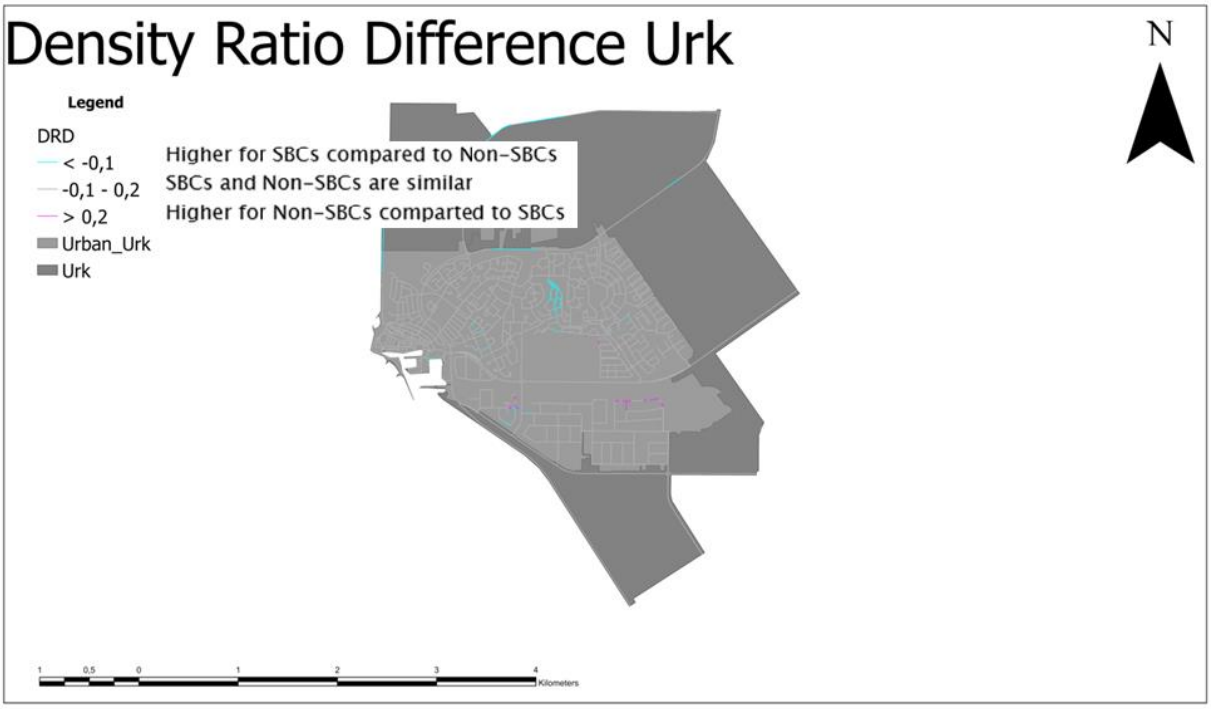


Figure A 8: Density Ratio Difference Urk

Figure A 9: Density Ratio Difference Noordoostpolder

Figure A 10: Density Ratio Difference Zeewolde

References

Abdel-Aty, M. A., & Radwan, A. E. (2000). Modeling traffic accident occurrence and involvement. In *Accident Analysis and Prevention* (Vol. 32). www.elsevier.com/locate/aap

Algurén, B., & Rizzi, M. (2022). In-depth understanding of single bicycle crashes in Sweden - Crash characteristics, injury types and health outcomes differentiated by gender and age-groups. *Journal of Transport & Health*, *24*(101320).

Alluri, P., Rihan, As. M., Saha, D., Wu, W., Huq, A., Nafis, S., & Gan, A. (2017). *Statewise Analysis of Bicycle Crashes*.

Alsop, J., & Langley, J. (2001). Under-reporting of motor vehicle traffic crash victims in New Zealand. In *Accident Analysis and Prevention* (Vol. 33). www.elsevier.com/locate/aap

Asadi, M., Ulak, M. B., Geurs, K. T., Weijermars, W., & Schepers, P. (2022). A comprehensive analysis of the relationships between the built environment and traffic safety in the Dutch urban areas. *Accident Analysis & Prevention*, *172*, 106683. https://doi.org/https://doi.org/10.1016/j.aap.2022.106683

Beck, B., Stevenson, M. R., Cameron, P., Oxley, J., Newstead, S., Olivier, J., Boufous, S., & Gabbe, B. J. (2019). Crash characteristics of on-road single-bicycle crashes: an under-recognised problem. *Injury Prevention*, *25*(5), 448–452. https://doi.org/10.1136/injuryprev-2018-043014

Blazquez, C. A., & Celis, M. S. (2013). A spatial and temporal analysis of child pedestrian crashes in Santiago, Chile. *Accident Analysis and Prevention*, *50*, 304–311. https://doi.org/10.1016/j.aap.2012.05.001

Boele-Vos, M. J., Van Duijvenvoorde, K., Doumen, M. J. A., Duivenvoorden, C. W. A. E., Louwerse, W. J. R., & Davidse, R. J. (2017). Crashes involving cyclists aged 50 and over in the Netherlands: An in-depth study. *Accident Analysis & Prevention*, *105*, 4–10. https://doi.org/10.1016/J.AAP.2016.07.016

BRON. (2024, September 5). *Verkeersongevallen - Bestand geRegistreerde Ongevallen Nederland*.

Brown, S. (2009). *Bicycle Tires and Tubes*.

Chen, P. (2015). Built environment factors in explaining the automobile-involved bicycle crash frequencies: A spatial statistic approach. *Safety Science*, *79*, 336–343. https://doi.org/10.1016/j.ssci.2015.06.016

Choudhary, J., Ohri, A., & Kumar, B. (2015). *Spatial and statistical analysis of road accidents hot spots using GIS*. https://www.researchgate.net/publication/291973317

Davidse, R., Duijvenvoorde, K. Van, Boele, M. J., Doumen, M. J. A., Duivenvoorden, C. W. A. E., & Louwerse, W. J. R. (2014). *r-2014-03a*.

De Rome, L., Boufous, S., Georgeson, T., Senserrick, T., Richardson, D., & Ivers, R. (2014). Bicycle Crashes in Different Riding Environments in the Australian Capital Territory. *Traffic Injury Prevention*, *15*(1), 81–88. https://doi.org/10.1080/15389588.2013.781591

DiGioia, J., Watkins, K. E., Xu, Y., Rodgers, M., & Guensler, R. (2017a). Safety impacts of bicycle infrastructure: A critical review. *Journal of Safety Research*, *61*, 105–119. https://doi.org/10.1016/j.jsr.2017.02.015

DiGioia, J., Watkins, K. E., Xu, Y., Rodgers, M., & Guensler, R. (2017b). Safety impacts of bicycle infrastructure: A critical review. *Journal of Safety Research*, *61*, 105–119. https://doi.org/10.1016/j.jsr.2017.02.015

Ding, H., Sze, N. N., Li, H., & Guo, Y. (2020). Roles of infrastructure and land use in bicycle crash exposure and frequency: A case study using Greater London bike sharing data. *Accident Analysis & Prevention*, *144*, 105652. https://doi.org/https://doi.org/10.1016/j.aap.2020.105652

Elvik, R., & Bjørnskau, T. (2017). Safety-in-numbers: A systematic review and meta-analysis of evidence. *Safety Science*, *92*, 274–282. https://doi.org/https://doi.org/10.1016/j.ssci.2015.07.017

Erdogan, S. (2009). Explorative spatial analysis of traffic accident statistics and road mortality among the provinces of Turkey. *Journal of Safety Research*, *40*(5), 341–351. https://doi.org/10.1016/j.jsr.2009.07.006

Erdogan, S., Yilmaz, I., Baybura, T., & Gullu, M. (2008). Geographical information systems aided traffic accident analysis system case study: city of Afyonkarahisar. *Accident Analysis and Prevention*, *40*(1), 174–181. https://doi.org/10.1016/j.aap.2007.05.004

Ermagun, A., & Levinson, D. (2018). An Introduction to the Network Weight Matrix. *Geographical Analysis*, *50*(1), 76–96. https://doi.org/10.1111/gean.12134

ESRI. (2024a, May 29). *Best practices for selecting a fixed distance band value*. ArcGIS Pro.

ESRI. (2024b, May 29). *How Cluster and Outlier Analysis (Anselin Local Moran's I) works*. ArcGIS Pro.

ESRI. (2024c, May 29). *Modeling spatial relationships*. ArcGIS Pro.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, *76*(3), 265–294. https://doi.org/10.1080/01944361003766766

Francke, A. (2022). Cycling during and after the COVID-19 pandemic. In *Advances in Transport Policy and Planning* (Vol. 10, pp. 265–290). Elsevier B.V. https://doi.org/10.1016/bs.atpp.2022.04.011

Gedamu, W. T., Plank-Wiedenbeck, U., & Wodajo, B. T. (2024). A spatial autocorrelation analysis of road traffic crash by severity using Moran's I spatial statistics: A comparative study of Addis Ababa and Berlin cities. *Accident Analysis and Prevention*, *200*. https://doi.org/10.1016/j.aap.2024.107535

GGD Flevoland. (2022, February 16). *Verkeersongevallen met ambulancezorg in Flevoland: puntlocatie's, kruispunten, vervoersmiddelen (2013 tm 2019)*.

Gildea, K., & Simms, C. (2021). Characteristics of cyclist collisions in Ireland: Analysis of a self-reported survey. *Accident Analysis & Prevention*, *151*, 105948. https://doi.org/10.1016/J.AAP.2020.105948

Ha, H. H., & Thill, J. C. (2011). Analysis of traffic hazard intensity: A spatial epidemiology case study of urban pedestrians. *Computers, Environment and Urban Systems*, *35*(3), 230–240. https://doi.org/10.1016/j.compenvurbsys.2010.12.004

Hauer, E. (2004). Statistical Road Safety Modeling. *Transportation Research Record*, *1897*(1), 81–87. https://doi.org/10.3141/1897-11

Hazaymeh, K., Almagbile, A., & Alomari, A. H. (2022). Spatiotemporal Analysis of Traffic Accidents Hotspots Based on Geospatial Techniques. *ISPRS International Journal of Geo-Information*, *11*(4). https://doi.org/10.3390/ijgi11040260

Heesch, K. C., Garrard, J., & Sahlqvist, S. (2011). Incidence, severity and correlates of bicycling injuries in a sample of cyclists in Queensland, Australia. *Accident Analysis & Prevention*, *43*(6), 2085–2092. https://doi.org/10.1016/J.AAP.2011.05.031

Hertach, P., Uhr, A., Niemann, S., & Cavegn, M. (2018). Characteristics of single-vehicle crashes with e-bikes in Switzerland. *Accident Analysis & Prevention*, *117*, 232–238. https://doi.org/https://doi.org/10.1016/j.aap.2018.04.021

Jacobsen, P. L. (2015). Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury Prevention*, *21*(4), 271–275. https://doi.org/10.1136/ip.9.3.205rep

Jiang, X., Yan, X., Huang, B., & Richards, S. H. (2011). Influence of curbs on traffic crash frequency on high speed roadways. *Traffic Injury Prevention* , *12*(4), 412–421.

Juhra, C., Wieskötter, B., Chu, K., Trost, L., Weiss, U., Messerschmidt, M., Malczyk, A., Heckwolf, M., & Raschke, M. (2012). Bicycle accidents - Do we only see the tip of the iceberg?: A prospective multi-centre study in a large German city combining medical and police data. *Injury*, *43*(12), 2026–2034. https://doi.org/10.1016/j.injury.2011.10.016

Kapousizis, G., Goodman, A., & Aldred, R. (2021). Cycling injury risk in Britain: A case-crossover study of infrastructural and route environment correlates. *Accident Analysis and Prevention*, *154*. https://doi.org/10.1016/j.aap.2021.106063

Keskin, F., Yenilmez, F., Çolak, M., Yavuzer, I., & Düzgün, H. Ş. (2011). Analysis of traffic incidents in METU campus. *Procedia - Social and Behavioral Sciences*, *19*, 61–70. https://doi.org/10.1016/j.sbspro.2011.05.108

Lakshmi, S., Srikanth, I., & Arockiasamy, M. (2019). Identification of Traffic Accident Hotspots using Geographical Information System (GIS). *International Journal of Engineering and Advanced Technology*. https://doi.org/10.35940/ijeat.B3848.129219

Lee, J., & Abdel-Aty, M. (2018). Macro-level analysis of bicycle safety: Focusing on the characteristics of both crash location and residence. *International Journal of Sustainable Transportation*, *12*(8), 553–560. https://doi.org/10.1080/15568318.2017.1407973

Lee, S.-I. (2001). s101090100064. *Geographical System*, *3*(369), 369–385.

Loidl, M., Wallentin, G., Wendel, R., & Zagel, B. (2016). Mapping bicycle crash risk patterns on the local scale. *Safety*, *2*(3). https://doi.org/10.3390/safety2030017

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. *Transportation Research Part A: Policy and Practice*, *44*(5), 291–305. https://doi.org/10.1016/j.tra.2010.02.001

Mohaymany, A. S., Shahri, M., & Mirbagheri, B. (2013). GIS-based method for detecting high-crash-risk road segments using network kernel density estimation. *Geo-Spatial Information Science*, *16*(2), 113–119. https://doi.org/10.1080/10095020.2013.766396

Møller, M., Janstrup, K. H., & Pilegaard, N. (2021). Improving knowledge of cyclist crashes based on hospital data including crash descriptions from open text fields. *Journal of Safety Research*, *76*, 36–43. https://doi.org/https://doi.org/10.1016/j.jsr.2020.11.004

Mukoko, K. K., & Pulugurtha, S. S. (2020). Examining the influence of network, land use, and demographic characteristics to estimate the number of bicycle-vehicle crashes on urban roads. *IATSS Research*, *44*(1), 8–16. https://doi.org/10.1016/j.iatssr.2019.04.001

Myhrmann, M. S., Janstrup, K. H., Møller, M., & Mabit, S. E. (2021). Factors influencing the injury severity of single-bicycle crashes. *Accident Analysis and Prevention*, *149*. https://doi.org/10.1016/j.aap.2020.105875

Naghawi, H. (2018). Negative Binomial Regression Model for Road Crash Severity Prediction. *Modern Applied Science*, *12*, 38. https://doi.org/10.5539/mas.v12n4p38

Narayanamoorthy, S., Paleti, R., & Bhat, C. R. (2013). On accommodating spatial dependence in bicycle and pedestrian injury counts by severity level. *Transportation Research Part B: Methodological*, *55*, 245–264. https://doi.org/10.1016/j.trb.2013.07.004

NWB. (2024). *The NWB products*.

Nyberg, P., Björnstig, U., & Bygren, L.-O. (1996). Road characteristics and bicycle accidents. *Scandinavian Journal of Social Medicine*, *24*(4), 293–301. https://doi.org/10.1177/140349489602400410

Ohlin, M., Algurén, B., & Lie, A. (2019). Analysis of bicycle crashes in Sweden involving injuries with high risk of health loss. *Traffic Injury Prevention*, *20*(6), 613–618. https://doi.org/10.1080/15389588.2019.1614567

Okabe, A., Okunuki, K. I., & Shiode, S. (2006). The SANET toolbox: New methods for network spatial analysis. *Transactions in GIS*, *10*(4), 535–550. https://doi.org/10.1111/j.1467-9671.2006.01011.x

Ormel, W., Klein Wolt, K., & den Hertog, P. (2008). *Enkelvoudige fietsongevallen; Een LIS-vervolgonderzoek*.

Ormel, W., Klein Wolt, K., & Den Hertog, P. (2008). *Enkelvoudige fietsongevallen. (Single-bicycle crashes)*.

Osama, A., & Sayed, T. (2017). Evaluating the Impact of Socioeconomics, Land Use, Built Environment, and Road Facility on Cyclist Safety. *Transportation Research Record*, *2659*(1), 33–42. https://doi.org/10.3141/2659-04

Petegem, J. H., Schepers, P., & Wijlhuizen, G. J. (2021). The safety of physically separated cycle tracks compared to marked cycle lanes and mixed traffic conditions in Amsterdam. *European Journal of Transport and Infrastructure Research*, *21*(3), 19–37.

Prasannakumar, V., Vijith, H., Charutha, R., & Geetha, N. (2011). Spatio-temporal clustering of road accidents: GIS based analysis and assessment. *Procedia - Social and Behavioral Sciences*, *21*, 317–325. https://doi.org/10.1016/j.sbspro.2011.07.020

Prati, G., Fraboni, F., De Angelis, M., & Pietrantoni, L. (2019). Gender differences in cyclists' crashes: an analysis of routinely recorded crash data. *International Journal of Injury Control and Safety Promotion*, *26*(4), 391–398. https://doi.org/10.1080/17457300.2019.1653930

Provincie Flevoland. (2016). *Mobiliteitsvisie 2030*.

Provincie Flevoland. (2024). *Feitelijk Flevoland, provincie Flevoland*. https://feitelijkflevoland.nl/dashboard/dashboard/bevolking

Pulugurtha, S. S., & Thakur, V. (2015). Evaluating the effectiveness of on-street bicycle lane and assessing risk to bicyclists in Charlotte, North Carolina. *Accident Analysis & Prevention*, *76*, 34–41. https://doi.org/https://doi.org/10.1016/j.aap.2014.12.020

Reurings, M., Stipdonk, drs H., Minnaard, F., & Eenink, ir R. (2012). *Waarom is de ontwikkeling van het aantal ernstig verkeersgewonden anders dan die van het aantal verkeersdoden?*

Rijkswaterstaat. (2022). *Handleiding product Bestand geRegistreerde Ongevallen Nederland (2)*.

Saha, D., Dumbaugh, E., & Merlin, L. A. (2020). A conceptual framework to understand the role of built environment on traffic safety. *Journal of Safety Research*, *75*, 41–50. https://doi.org/https://doi.org/10.1016/j.jsr.2020.07.004

Schepers, P. (2008). *De rol van infrastructuur bij enkelvoudige fietsongevallen*.

Schepers, P. (2012). Does more cycling also reduce the risk of single-bicycle crashes? *Injury Prevention*, *18*(4), 240. https://doi.org/10.1136/injuryprev-2011-040097

Schepers, P., Agerholm, N., Amoros, E., Benington, R., Bjørnskau, T., Dhondt, S., de Geus, B., Hagemeister, C., Loo, B. P. Y., & Niska, A. (2015a). An international review of the frequency of single-bicycle crashes (SBCs) and their relation to bicycle modal share. *Injury Prevention*, *21*(E1), e138–e143. https://doi.org/10.1136/injuryprev-2013-040964

Schepers, P., Agerholm, N., Amoros, E., Benington, R., Bjørnskau, T., Dhondt, S., de Geus, B., Hagemeister, C., Loo, B. P. Y., & Niska, A. (2015b). An international review of the frequency of single-bicycle crashes (SBCs) and their relation to bicycle modal share. *Injury Prevention*, *21*(E1), e138–e143. https://doi.org/10.1136/injuryprev-2013-040964

Schepers, P., & den Brinker, B. (2011). What do cyclists need to see to avoid single-bicycle crashes? *Ergonomics*, *54*(4), 315–327. https://doi.org/10.1080/00140139.2011.558633

Schepers, P., & Klein Wolt, K. (2012). *Single-Bicycle Crash Types and Characteristics*. www.wocref.org/cri

Shinar, D., Valero-Mora, P., van Strijp-Houtenbos, M., Haworth, N., Schramm, A., De Bruyne, G., Cavallo, V., Chliaoutakis, J., Dias, J., Ferraro, O. E., Fyhri, A., Sajatovic, A. H., Kuklane, K., Ledesma, R., Mascarell, O., Morandi, A., Muser, M., Otte, D., Papadakaki, M., … Tzamalouka, G. (2018). Under-reporting bicycle accidents to police in the COST TU1101 international survey: Cross-country comparisons and associated factors. *Accident Analysis and Prevention*, *110*, 177–186. https://doi.org/10.1016/j.aap.2017.09.018

Siddiqui, C., Abdel-Aty, M., & Choi, K. (2012). Macroscopic spatial analysis of pedestrian and bicycle crashes. *Accident Analysis and Prevention*, *45*, 382–391. https://doi.org/10.1016/j.aap.2011.08.003

Siddiqui, C., Abdel-Aty, M., & Choi, K. (2014). Implications of Pedestrian Safety Planning Factors in Areas with Minority and Low-Income Populations. *International Journal of Sustainable Transportation*, *8*(5), 360–381. https://doi.org/10.1080/15568318.2012.702853

Siegel, A. F. (2016). *Practical business statistics*. AcademicPress.

Strauss, J., & Mirando-Moreno, L. F. (2012). Effect of intersection designs on cyclist injury risk. *Proceedings of the 22nd Canadian Multidisciplinary Road Safety Conference*.

Thakali, L., Kwon, T. J., & Fu, L. (2015). Identification of crash hotspots using kernel density estimation and kriging methods: a comparison. *Journal of Modern Transportation*, *23*(2), 93–106. https://doi.org/10.1007/s40534-015-0068-0

Twisk, D., Vlakveld, W., Dijkstra, A., Reurings, M., & Wijnen, W. (2013). *From bicycle crashes to measures Brief overview of what we know and do not know (yet)*.

Uijtdewilligen, T., Ulak, M. B., Wijlhuizen, G. J., Bijleveld, F., Dijkstra, A., & Geurs, K. T. (2022). How does hourly variation in exposure to cyclists and motorised vehicles affect cyclist safety? A case study from a Dutch cycling capital. *Safety Science*, *152*, 105740. https://doi.org/https://doi.org/10.1016/j.ssci.2022.105740

Uijtdewilligen, T., Ulak, M. B., Wijlhuizen, G. J., Bijleveld, F., Geurs, K. T., & Dijkstra, A. (2023). Examining the crash risk factors associated with cycling by considering spatial and temporal disaggregation of exposure: Findings from four Dutch cities. *Journal of Transportation Safety and Security*. https://doi.org/10.1080/19439962.2023.2273547

Ulak, M. B., Ozguven, E. E., & Spainhour, L. (2017). Age-Based Stratification of Drivers to Evaluate the Effects of Age on Crash Involvement. *Transportation Research Procedia*, *22*, 551–560. https://doi.org/10.1016/j.trpro.2017.03.044

Ulak, M. B., Ozguven, E. E., Vanli, O. A., Dulebenets, M. A., & Spainhour, L. (2018). Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations. *Accident Analysis & Prevention*, *121*, 1–13. https://doi.org/https://doi.org/10.1016/j.aap.2018.08.031

Useche, S. A., Montoro, L., Alonso, F., & Tortosa, F. M. (2018). Does gender really matter? A structural equation model to explain risky and positive cycling behaviors. *Accident Analysis & Prevention*, *118*, 86–95. https://doi.org/https://doi.org/10.1016/j.aap.2018.05.022

Utriainen, R. (2020). Characteristics of Commuters' Single-Bicycle Crashes in Insurance Data. *Safety*, *6*(1). https://doi.org/10.3390/safety6010013

Utriainen, R., O'Hern, S., & Pöllänen, M. (2023). Review on single-bicycle crashes in the recent scientific literature. *Transport Reviews*, *43*(2), 159–177. https://doi.org/10.1080/01441647.2022.2055674

Vahedi Saheli, M., & Effati, M. (2021). Segment-Based Count Regression Geospatial Modeling of the Effect of Roadside Land Uses on Pedestrian Crash Frequency in Rural Roads. *International Journal of Intelligent Transportation Systems Research*, *19*(2), 347–365. https://doi.org/10.1007/s13177-020-00250-1

Vandenbulcke, G., Thomas, I., de Geus, B., Degraeuwe, B., Torfs, R., Meeusen, R., & Int Panis, L. (2009). Mapping bicycle use and the risk of accidents for commuters who cycle to work in Belgium. *Transport Policy*, *16*(2), 77–87. https://doi.org/https://doi.org/10.1016/j.tranpol.2009.03.004

Vandenbulcke, G., Thomas, I., & Int Panis, L. (2014). Predicting cycling accident risk in Brussels: A spatial case-control approach. *Accident Analysis and Prevention*, *62*, 341–357. https://doi.org/10.1016/j.aap.2013.07.001

Wang, H., Chang, S. K. J., De Backer, H., Lauwers, D., & De Maeyer, P. (2019). Integrating Spatial and Temporal Approaches for Explaining Bicycle Crashes in High-Risk Areas in Antwerp (Belgium). *Sustainability*, *11*(13). https://doi.org/10.3390/su11133746

Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident Analysis & Prevention*, *44*(1), 19–29. https://doi.org/https://doi.org/10.1016/j.aap.2010.11.010

Wei, F., & Lovegrove, G. (2013). An empirical tool to evaluate the safety of cyclists: Community based, macro-level collision prediction models using negative binomial regression. *Accident Analysis and Prevention*, *61*, 129–137. https://doi.org/10.1016/j.aap.2012.05.018

Welleman, A. G., & Dijkstra, A. (1988). *VEILIGHEIDSASPECTEN VAN STEDELIJKE FIETSPADEN*.

Wijlhuizen, G. J., & Bos, D. N. M. (2020). *Verkeersslachtoffers in Flevoland*. www.swov.nl

World Health Organization. (2022). *Walking and cycling: latest evidence to support policy-making and practice*.

Xie, Z., & Yan, J. (2008). Kernel Density Estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems*, *32*(5), 396–406. https://doi.org/10.1016/j.compenvurbsys.2008.05.001

Yang, B. Z., & Loo, B. (2016). Land use and traffic collisions: A link-attribute analysis using Empirical Bayes method. *Accident Analysis & Prevention*, *95*, 236–249. https://doi.org/10.1016/j.aap.2016.07.002

Zandi, K., Tavakoli Kashani, A., & Okabe, A. (2023). Influence of Traffic Parameters on the Spatial Distribution of Crashes on a Freeway to Increase Safety. *Sustainability (Switzerland)*, *15*(1). https://doi.org/10.3390/su15010493

Zhang, Y., Li, H., & Ren, G. (2023). Analyzing the injury severity in single-bicycle crashes: An application of the ordered forest with some practical guidance. *Accident Analysis and Prevention*, *189*. https://doi.org/10.1016/j.aap.2023.107126

Zhao, Y., Miyahara, T., Mizuno, K., Ito, D., & Han, Y. (2021). Analysis of car driver responses to avoid car-to-cyclist perpendicular collisions based on drive recorder data and driving simulator experiments. *Accident Analysis & Prevention*, *150*, 105862. https://doi.org/https://doi.org/10.1016/j.aap.2020.105862

Zwerling, C., Peek-Asa, C., Whitten, P. S., Choi, S.-W., Sprince, N. L., & Jones, M. P. (2005). Fatal motor vehicle crashes in rural and urban areas: decomposing rates into contributing factors. *Injury Prevention*, *11*(1), 24–28. https://doi.org/10.1136/ip.2004.005959