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FINDING THE SAFEST PATHS IN KHAYELITSHA TOWNSHIP, WESTERN CAPE PROVINCE, SOUTH AFRICA

by

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Declaration

I, Kayla Theron, declare that the dissertation/thesis, which I, hereby submit for the degree MSc. in Geoinformatics at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

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Executive summary

Crime is a major problem in Khayelitsha, a township located near Cape Town in the Western Cape province of South Africa. Moreover, residents in Khayelitsha constantly walk to get around the township, either to their transit stops or other daily destinations, placing them at increased risk of victimisation during their commute. To address this, this study aimed to determine the safest walking routes between the same origin and destination point locations in Khayelitsha. Three methods were proposed. Method 1 used historical crime incidents to identify high crime streets that should be avoided when finding the safest route to walk. In this method, each street segment had a corresponding crime count per metre and this crime measure was used as the cost of travel. The route with the lowest crime count per metre in total was regarded as the safest. In Method 2, the location of a number of so-called 'risky facilities' was used to determine risk on street segments rather than using historical crime incidents, like in Method 1. This method incorporated 50-metre buffer areas around all risky facilities and treated these as 'danger zones'. So, any street segment that passed through these danger zones were deemed as 'unsafe' and should be avoided in the route analysis. In Method 2, the danger zones were all given an equal weight (of two), assuming that all risky facilities had the same influence on crime (i.e., they were all equally as unsafe as each other). Therefore in this method the shortest route that traversed the lowest number of danger zones along the way was considered the safest.

On the other hand, Method 3 used both historical crime incidents as well as the location of risky facilities to determine risk. In this final method, the historical crime incident data was used to weight each risky facility to demonstrate its relative association with crime in Khayelitsha. This was done by calculating the average

number of crimes that occurred within 50 metres of a risky facility and converting these averages to a weight between one and seven. In this method, the shortest route that traversed the lowest number of *weighted* danger zones was regarded as the safest. The safest routes during the day, night, weekday and weekend were also determined and compared.

The safest route generated in Method 1 was the longest walking route but encountered just under 300 historical crime incidents in total. On the other hand, the safest routes generated in Method 2 and 3 encountered roughly double the amount of crime, with exactly 601 and 699 historical crime incidents, respectively. Overall, the route generated in Method 3 had the highest crime count per metre when compared to all the alternative safest routes generated in this research. When crime was filtered temporally, there were slight differences in the safest routes generated in Method 1. Surprisingly, this was not the case in Method 3, where the safest routes remained the same for daytime, night-time, weekdays and weekends. Total walking distance, historical crime incidents, number of risky facilities, or type of risky facilities can each act as pedestrian preferences when selecting a route to walk. Each of these aspects impact the resultant ‘safest’ walking route in Khayelitsha. Future work should test these safe navigation methods in other geographical contexts with other modes of transport, crime data and types of facilities. It is encouraged that these methods be included in mobile navigation applications so that residents in Khayelitsha can be advised on the safest walking routes between their personal origin and destination point locations.

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Chapter 1: Introduction

1.1 Background

A number of theories and laws have been established by criminologists to explain and interpret the spatial distribution of crime. Weisburd's (2015) '*law of crime concentration at place*' is one well-known law which suggests that a certain percentage of places accounts for a fixed percentage of crime (e.g., 5 percent of street segments accounts for 50 percent of crime across different cities). Indeed, crime has been found to be concentrated in small bandwidths of percentages at very particular places across various units of analysis (from macro- to micro-places) (see Braga & Weisburd 2010; Brantingham & Brantingham 1998; Chainey *et al.* 2019; Favarin 2018; Groff, Weisburd & Yang 2010; Sherman, Gartin & Buerger 1989; Theron, Breetzke, Snyman & Edelstein 2023; Umar, Johnson & Cheshire 2021; Weisburd & Amram 2014; Wuschke, Anderson & Brantingham 2021). Spatial criminology research has historically focused on examining crime within larger units of analysis such as cities and neighbourhoods. At this coarser level of aggregation, crime has also been found to spatially concentrate (Braga & Weisburd 2010; Brantingham & Brantingham 1998; Breetzke & Edelstein 2019). However, researchers have begun to increasingly notice that within these larger geographic areas, crime is also spatially clustered (Andresen & Malleson 2011; Braga, Papachristos & Hureau 2014; Brantingham & Brantingham 1999; Crow & Bull 1975; Curmen, Andresen & Brantingham 2015; Kim & Hipp 2018). That is, certain public facilities and street blocks within a larger city or neighbourhood experience higher crime concentrations than other micro locations within a larger geographic area. Consequently, only a particular micro-environment (i.e., street) within a neighbourhood may be responsible for the majority of crime occurring there with a combination of these high crime micro-places causing the larger neighbourhood itself to be perceived as being criminogenic; a problem known as 'averaging' (see Weisburd, Morris & Groff 2009).

There has, therefore, recently been a shift in spatial criminology research away from analysis of crime at the coarse macro-level (neighbourhood) to more micro-level (street) examinations. Indeed, street segments and addresses, in particular, have been increasingly used to examine crime. This increased acknowledgement that finer street segments may provide a more accurate, and perhaps nuanced, indication of crime risk has led to a plethora of studies examining crime concentrations at the street segment level of spatial aggregation (Chainey *et al.* 2019; de Melo *et al.* 2015; Favarin 2018; Umar *et al.* 2021; Weisburd, Lawton & Ready 2012; Weisburd & White 2019; Wuschke *et al.* 2021). The vast majority of these past research studies have, however, been undertaken in the developed world, with much less research been undertaken examining street level crime risk in less developed contexts.

A number of spatial theories of crime have been used to explain the spatial distribution of crime at the street segment level including the *routine activity theory* and *crime pattern theory*. The routine activity theory of Cohen and Felson (1979) states that crime is most likely to occur when three elements converge in space and time, namely motivated offenders, suitable targets and the lack of capable guardianship. Aligned to this theory is the crime pattern theory of Brantingham and Brantingham (1991) which motivates that places that are visited by individuals on a daily basis become 'activity nodes' and the areas in which these nodes fall become 'awareness spaces' and as a result, motivated offenders become familiar with these comfort zones and are said to most likely commit crime in these spaces. Key within crime pattern theory are the concepts of 'crime generators' and 'crime attractors'.

Both places increase the risk of crime occurring due mainly to the fact that they attract a large number of motivated offenders and suitable targets to a particular location. The former places attract a considerable amount of people who do not intend to commit a crime at that place necessarily but increase the risk of crime in these locations due to the increased number of potential targets, while the latter places attract motivated offenders for nefarious reasons.

Crime generators in particular can include facilities such as shopping malls, entertainment venues, office blocks, transportation stops, parking lots, sporting grounds, high schools, highway offramps and neighbourhood parks, while crime attractors include liquor outlets, drug trading points, prostitution districts, insecure commercial/business parking lots, pawn stores, homeless shelters, bars, shops that deal with cash, substance abuse rehabilitation centres and halfway houses, hairdresser and beauty salons, convenience stores, petrol garages and fast-food outlets. Most crime generators and attractors occur on streets which makes this micro-level of spatial aggregation, arguably, the most important to examine in terms of crime risk. Indeed, travelling on streets with a high risk of crime can lead to increased victimisation.

This risk of victimisation at the street level can increase based on the two most common preferences that users have when selecting a route between an origin and destination point: namely, distance and time. Recent studies have, however, incorporated other factors which may be considered when choosing a route to travel including scenic beauty (Amirgholy *et al.* 2017; Chen *et al.* 2021), vehicle/pedestrian crash data (Sarraf & McGuire 2020) and, increasingly, safety considerations such as crime risk (de Souza *et al.* 2019; Shah *et al.* 2011).

South Africa is a country synonymous with crime. While official crime statistics for 2022/23 indicate that crime overall is on the decrease, certain categories of crime such as murder, sexual offences and assault continue to rise, with murder remaining particularly high with roughly 45 murders being committed per day in the country (South African Police Services (SAPS) 2023). Crime is also heavily concentrated in certain regions of the country, notably being in townships which most often experience a disproportionate amount of crime. The township of Khayelitsha, located roughly 30 kilometres from Cape Town, is one such location. In fact, crime is a major concern in Khayelitsha with the main policing precinct consistently being among the most violent precincts in the country with contact crime[1] in particular almost double the national average (Crime Hub 2021). Despite its high levels of crime, recent research in Khayelitsha has, however, shown how crime spatially concentrates in a relatively few number of streets in the township (see Theron *et al.* 2023) providing some initial local evidence of the 'law of crime concentration at places'. Identifying which streets are more dangerous than others is important as residents can reduce their risk of victimisation by using safer pathways.

Many residents in Khayelitsha rely on walking to get around the township. The City of Cape Town's Mayoral Committee for Transport stated how every person's journey in Khayelitsha starts with walking, whether it be from home to a transit stop, to school or to work (City of Cape Town, Media Office 2021). In fact, walking is the main mode of transport for more than eighty percent of children residing in Khayelitsha (Koekemoer *et al.* 2017). Moreover, recent research has found that certain types of facilities in the township such as schools, recreation hubs and transit

[1] 'Contact crimes' refer to when a person or people are injured/harmed or threatened with injury/harm during the commission of a crime. A further sub-category of 'contact-related crime' is used for violent crimes committed against property with the intention of causing damage to a person, for example arson or malicious damage to property.

interchanges can act as crime attractors (see Breetzke & Edelstein 2022) increasing the risk of victimisation of residents walking along streets with these facilities located adjacent to them.

1.2 Problem Statement

Crime is significant in Khayelitsha. Current research has shown how crime concentrates at the neighbourhood (Breetzke & Edelstein 2019) and street (Theron *et al.* 2023) level in the township. Knowing which streets in particular experience a disproportionate amount of crime can highlight problematic areas within the township and indicate which streets pedestrians should use or avoid when commuting. This knowledge presents an opportunity to use spatial analytic techniques such as network analyses to determine which routes would be safest for residents to use in Khayelitsha. It is currently unknown which routes are safest for people to walk between two locations (specifically the two pre-determined origin and destination locations in this research) in the township.

1.3 Research Aim and Objectives

The main aim of this research was to determine the safest walking routes between the same origin and destination point locations in Khayelitsha. The safest route(s) were determined based on either 1) historical crime risk, 2) the location of 'risky facilities' or 3) a combination of historical crime risk and 'risky facilities'. Three different methods were used in order to determine safe walking routes in Khayelitsha.

The research objectives to achieve the aim are outlined below:

> Objective 1: Source and map, the relevant spatial data (crime and facilities) required for the analysis

Objective 2: Filter crime data by all crime, daytime crime, night-time crime, weekday crime and weekend crime

Objective 3: Snap crime incidents to the nearest street segment and calculate a crime count per metre per street segment per crime period

Objective 4: Determine the safest route between two points in Khayelitsha based on historical crime data (Method 1)

Objective 5: Create danger zones around each risky facility in Khayelitsha

Objective 6: Determine the safest route between two points in Khayelitsha based on the location of equally risky facilities (Method 2)

Objective 7: Identify which facilities have the greatest association with crime and calculate a weight for each facility type to represent their corresponding association with crime (per crime period)

Objective 8: Determine the safest route between two points in Khayelitsha based on the location of weighted risky facilities (Method 3)

Objective 9: Map and compare the safest routes determined in each of the three methods

1.4 Significance of Research

Khayelitsha is plagued by high rates of crime. This research proposes three methods of reducing the risk of victimisation of residents by delineating safe walking routes in the township. The findings of this study indicated which streets in Khayelitsha were most crime prone with significant implications for policing. Indeed, streets identified as having disproportionate crime should be the primary focus of hotspot policing interventions and policies aimed at reducing crime risk in this community. Indeed, police vehicles should patrol certain high-risk streets more often in order to diminish the number opportunities for crime. Importantly, this research shows that policing intervention does not need to take place at the neighbourhood level in order to have an exponential effect but can rather occur at the finer street segment level to have the greatest effect. Thus, maximising resources, that are often scant in uniformly poor locations such as Khayelitsha. Since only a select few street segments experienced such high concentrations of crime, policing resources can be efficiently distributed to those locations.

Consequently, examining crime on individual street segments also allows for the identification of safer routes for pedestrians to traverse. Inevitably, however, even these safest routes may contain a number of ‘high risk’ sections. Although risky areas may not always be avoided completely, knowing the exact location of these areas can help caution pedestrians to be extra vigilant while traversing more crime prone street segments. The three methods proposed in this research can also be used in future mobile navigation applications where safety can be set as a user preference when determining routes between personal origin and destination point locations.

Chapter 2: Literature Review

This literature review chapter first outlines a number of spatial theories of crime and then examines the various units of analysis commonly used in spatial criminology. Finally, the chapter highlights important concepts of graph theory and different approaches to safe routing and network analyses.

2.1 Crime and Space

It is well accepted that place directly influences criminal behaviour (see Favarin 2018; Groff *et al.* 2010; Shukla *et al.* 2019; Weisburd & Amram 2014; Weisburd & White 2019) with crime tending to concentrate in certain areas (Groff *et al.* 2010; Jones & Pridemore 2019; Song *et al.* 2017). Indeed, a large number of studies from across the world have found that crime is spatially concentrated in a relatively low number of locations (Brantingham & Brantingham 1995; Chainey *et al.* 2019; Curman, Andresen, & Brantingham 2015; de Melo *et al.* 2015; Favarin 2018; Groff *et al.* 2010, Umar *et al.* 2020; Weisburd 2015; Weisburd, Groff & Yang 2014; Weisburd *et al.* 2004; Wuschke *et al.* 2021). Informed by these studies and his own work, Weisburd (2015), coined the 'law of crime concentration at place' moniker which refers to the fact that crime most often concentrates in small bandwidths of percentages representing certain cumulative proportions of crime occurring at various spatial scales ranging from macro- (neighbourhood) to micro-level (street segments) units of analysis. It was the initial work of Sherman *et al.* (1989), who shifted the focus in criminology research from macro- to micro-places with spatial crime research now commonly occurring at the street segment or address level of aggregation.

A number of theories have been developed over the past 50 years that have 'place' at its core. Key among them is the *routine activity theory* of Cohen and Felson (1979). According to this theory three essential elements are required to converge in space and time to increase the risk of crime: a motivated offender, a suitable target and the lack of capable guardianship – these collectively create an ideal opportunity for crime to take place. The routine activity theory argues that crime concentration is reliant on the space-time aspects that impact the frequency at which these three elements intersect. Importantly, there needs to be co-occurrence between victims and offenders with regards to 'rhythm' (pattern of events), 'tempo' (number of events across time) and 'timing' (exact overlap between victim and offender activities) in order for the risk of crime to increase.

Another theory commonly used to explain spatial crime concentrations is the *crime pattern theory* of Brantingham and Brantingham (1991). This theory attempts to examine the relationship between urban spaces and criminal behaviour using concepts such as 'activity nodes' and 'awareness spaces.' Activity nodes refer to the places visited by individuals on a daily basis and where most of their time is spent, such as workplaces, schools and shopping malls. By moving to and from these 'nodes', offenders become accustomed to these certain spaces - forming awareness spaces - and are more likely to target victims moving in and around these areas too.

Related to crime pattern theory is the notion of 'distance decay' which refers to the fact that offenders build up a 'cognitive map' of the areas in which they operate (see Tompson, Patridge & Shepherd 2009). Knowing an area gives offenders an added advantage, making them feel more in control when committing a crime with the further a potential offender is from their familiar routes, the less likely they are to commit a crime (Groff *et al.* 2010; Rengert, Piquero & Jones 1999). These opportunities and routine movements are at the forefront of most research studies in the attempt to understand crime at place. Finally, another important component of crime pattern theory is the notion of 'crime generators' and 'crime attractors'. These concepts are expanded on in the following sub-section as they play a key role in identifying safest routes in Khayelitsha.

2.2 Crime generators and attractors

Crime generators are sites or facilities that attract a considerable amount of people who do not intend to commit a crime at that place necessarily but increase the risk of crime in these locations due to the increased number of potential targets. Conversely, crime attractors are facilities, sites or structures that attract motivated offenders. Brantingham and Brantingham (1995) specifically call these offenders 'intending offenders' as they explicitly try to commit a crime at these locations. Intending offenders are willing to travel great distances to reach their targeted destinations. These crime generators and attractors are collectively referred to as 'risky facilities' by Eck, Clarke and Guerette (2007) and are said to appear as hot spots when analysing crime patterns across a city. A number of crime generators and attractors that have been highlighted in the extant literature and are further discussed in detail below. Indeed there are numerous other facilities that are not included, but for space considerations, some key crime generators and attractors are outlined.

2.2.1 Alcohol Outlets

One of the most well-known crime attractors are alcohol outlets. Previous research has shown a positive association between crime and alcohol outlets in a variety of contexts (see Britt *et al.* 2005; Cameron 2022; Conrow, Aldstadt & Mendoza 2015; Franklin *et al.* 2010; Jennings *et al.* 2014; Zhu, Gorman & Horel 2004). Indeed, previous research has shown that areas within a close proximity of alcohol outlets, tend to experience a greater amount of serious violent crime as opposed to areas with less accessibility to these outlets (Day *et al.* 2012; Gorman *et al.* 2001; Speer *et al.* 1998). It has also been found that poorer unstable communities are more vulnerable to crime near alcohol outlets than more affluent neighbourhoods (Franklin *et al.* 2010; Gruenewald *et al.* 2006; Lipton *et al.* 2013).

Interestingly, previous research has also demonstrated that the type of alcohol outlet as well as its operating hours both impact violent crime. For example, in Washington, DC, Franklin *et al.* (2010) found different relationships between on- and off site alcohol outlets and violent crime. For instance, on- and off site alcohol outlets were found to be positively associated with homicide, assault and sexual offence, while being significantly associated with robbery. Later, Wheeler (2018) found that off-premise and on-premise alcohol outlets had the same influence on crime with both types of outlets increasing the risk of crime White, Gainey & Triplett (2015) found a strong significant positive association between the number of street crimes and the number of on-premise and off-premise alcohol outlets in Norfolk, Virginia while Trangenstein *et al.* (2018) found that violent crime had a greater association with off-premise alcohol outlets than with on-premise alcohol outlets in Baltimore, MD.

In terms of opening hours, Schofield and Denson's (2013) found that the later alcohol outlets remained open in New York (especially after one o'clock in the morning), the more influence they have on violent crime while de Goeij *et al.* (2015) found that extending the operating hours of alcohol outlets by just one hour was associated with a roughly 30 percent more alcohol-related injuries in Amsterdam, The Netherlands.

Locally, alcohol outlets have also been found to be associated with various types of crime (Herrick & Charman 2013; Murhula & Nunlall 2021; Parry, Morojele & Jernigan 2008). Already in 1996 the SAPS (1997) noted that shebeens were linked to murder and other violent crime in the Western Cape province, while Shaw and Louw (1997) found that child abuse and sexual crime was associated with alcohol use in the Northern Cape. Shebeens (i.e., bars in South Africa) in particular are known to be linked to violence and tend to be vulnerable to robbery due to being primarily cash based (Herrick & Charman 2013). The SAPS (2020) reported several types of crimes involving alcohol usage during 2019 and 2020, with hundreds of rapes, murders and attempted murders, as well as thousands of assault charges. Notably, when alcohol was banned for a few months during the COVID-19 (Coronavirus 2019) pandemic in South Africa, crime statistics dropped considerably (South African Police Service (SAPS) 2023).

2.2.2 Shopping Malls

Shopping malls have frequently been found to be associated with crime (Brantingham, Brantingham & Wong 1990; Peiser & Xiong 2020; Savard & Kennedy 2014). According to Button (2008), shopping malls generate crime due to their openness and ease of access. This means that numerous suppliers, workers and customers enter and exit the mall frequently leading to more anonymity and interaction. Certain structural features of shopping malls have also been found to contribute to its potential vulnerability including multiple access points, neighbouring parking lots, dark corridors, corners and aisles that cannot be easily monitored (see Button 2008). It should also be noted that the environment in which shopping malls are located can also influence the potential vulnerability of the mall to increased crime risk. For example, if a shopping mall is located in a low-income neighbourhood the probability of crime occurring at the particular local shopping malls is increased (see Ceccato *et al.* 2018; Mago *et al.* 2014). Interestingly, previous research has found how motivated offenders tend to commit crime on their way to shopping malls (see Mago *et al.* 2014).

Locally, there is some evidence that shopping malls act as generators of crime (Citizen Reporter 2022; Dayimani 2023; Gounden 2023; Hlangu 2023; Lindeque & Ntshidi 2021; McCain 2023; Modise 2023; Penny 2022; Phaliso 2023; Pijoos 2023; PropertyWheel_GLP 2018; Sefularo 2022; Seleka 2022; Thurtell 2021). For example, Lutchminarain (2012) found that various violent crimes such as cash-in-transits, store and ATM robberies, and vehicle hijacking were spatially associated with shopping malls. The researcher also discovered that some security staff and other staff members of shopping malls themselves collude with criminal syndicates to enable crime in and around these facilities. In Gauteng, Snyders and Landman (2018) studied crime patterns at shopping nodes in two neighbourhoods of the City of Tshwane and found evidence of crime hotspots around shopping malls in Kilner Park and Queenswood, with the latter being more severe.

2.2.3 Transit Facilities

Transit facilities such as train stations, bus stops and taxi stops have also been found to act as crime generators (Ceccato & Newton 2015; Gallison & Andresen 2017; Groff & Lockwood 2014; Irvin-Erickson & La Vigne 2015; Newton, Partridge & Gill 2014). Brantingham and Brantingham (1993; 1995) emphasise that individuals from numerous thoroughfares converge at these transit points which in turn creates opportunities for crime to take place since there is a large pool of potential victims and offenders. For example, Xu and Griffiths (2017) found bus stops in Newark, NJ, to be associated with an increased number of shootings while in Indianapolis, Indiana, Stucky and Smith (2017) found that bus stops were associated with increased sexual (rape), violent (aggravated assault) and property crime (robbery, burglary, theft). In Los Angeles, California, Loukaitou-Sideris (2004) conducted research on 202 local bus commuters (95 female and 107 male) and found that roughly one third were victims of crime at a transit location. Outside the US, Natarajan *et al.* (2015) found an increased risk of crime around bus stops in El Salvador. In their research, these facilities were described as ill maintained and dominated by vandalism, poor lighting, scattered refuse, unpaved flooring, passenger turmoil/overcrowding, numerous beggars and street hawkers. Finally, the socio-economic conditions of the neighbourhood in which the transit stop is located has also been found to increase crime risk at these facilities. For example, transit related crimes are more likely to occur in city centres that are known to have high levels of criminal activity (Pearlstein & Wachs 1982). Badiora, Ojewale and Okunola (2015) explain that crime can occur while walking between, to or from transport stops as well as on board the respective vehicle. Kruger and Landman (2007) further support this claim by stating that people who reside in poorer communities often live far from their place of employment in South Africa and therefore tend to travel long distances on public transport. Therefore, these commuters "are exposed to victimisation on busses, trains or minibus taxis, while changing from one mode of transport to another at stations, or when walking from drop-off points to their places of work or to their homes" (Kruger & Landman 2007:116).

Anecdotal evidence in South Africa suggests that public transportation facilities, especially taxi ranks, are criminogenic settings commonly targeted by offenders for crimes ranging from pickpocketing to more serious offences such as rape. Page (2001) also found that one out of six commuters have been victims of crime in

Durban. Moreover, findings from customer preference surveys (2001 and 2002) in Cape Town have shown that passengers tend to have negative stances towards public transport modes specifically with regards to crime and their safety (see Lombard & Hugo 2002). According to the first National Household Travel Survey conducted in 2003 crime was one of the main reasons why commuters chose not to use public transport in South Africa.

Attempts have been made to formalise the public transport sector in South Africa by, among others, creating bus services such as the MyCiti bus service (also known as the Bus Rapid Transport system), implemented in the City of Cape Town, in the Western Cape in 2010. This alternative public transport initiative was sparked by the realisation that the initial public transportation system would not be able to handle the enormous amount of tourists visiting Cape Town during the FIFA World Cup in 2010, which was hosted by South Africa. The municipality designed the MyCiti bus service to be a safer, more reliable, accessible, affordable and convenient form of transport than the taxi services (City of Cape Town 2023). However, the implementation of the system has severely impacted the taxi industry in Cape Town as taxis were banned from their original routes if they overlapped with the MyCiti bus service and some taxis stated that their businesses were ‘dying’ as commuters would rather take a MyCiti bus instead of their taxis (Bristow 2015). This led to the government’s decision to compensate (monetarily) those taxi drivers who were directly impacted and simultaneously offered them job positions as MyCiti bus drivers. Unfortunately, partially impacted drivers were not compensated, therefore fuelling anger towards this competing transport service; and violence towards it (Bristow 2015).

Currently, there is ongoing violence between the MyCiti bus service and taxi owners and operators. Roughly 70 buses were damaged between November 2022 and January 2023 by individuals throwing stones at the passing buses predominantly on routes running from Mitchells Plain and Khayelitsha to the Civic Centre bus stop (Independent Online, 2023). Numerous other reports have also covered the many violent acts targeting the MyCiti bus service (Mkalipi 2021; Monama 2022; Viljoen 2022) including a violent shooting in Camps Bay in October 2022 (Evans 2022) and stoning of three MyCiti buses in Hout Bay (Viljoen 2022). These protesters demanded that only taxis serve Hout Bay and that no MyCiti bus can run in that area.

2.2.4 Parks

Parks and surrounding areas have also been found to be associated with crime and act as crime generators (Boessen & Hipp 2018; Ceccato 2014; Ellickson 1996; Felson & Boba 2010). For example, Groff and McCord (2012) found that crime was concentrated near neighbourhood parks in Philadelphia and that just over 90% of parks experienced violent crime. The researchers also noted, however, that some park features were actually associated with lower crime levels. They found that parks that incorporate amenities such as a recreation centre and tennis courts appeal to more legitimate park goers and this reduces crime risk. However, according to Loukaitou-Sideris (2004) parks are essentially unoccupied vacant land that provide offenders with the belief that they will remain ‘out of sight’. In addition to the facility itself, the access routes to parks are also commonly viewed as unsafe and can create favourable opportunities for crime.

In the South African context, Mashalaba (2013) found how residents of the Galeshewe township in Kimberley, viewed parks as unsafe vacant land rather than a recreational space. Moreover, findings by Perry, Moodley and Bob (2008) as well as Pillay and Pahlad (2014) showed that parks were regarded as crime hotspots in Durban, South Africa. Perry *et al.* (2008) conducted 100 surveys and a focus group discussion based on households who lived near parks and other vacant land in Reservoir Hills, Durban, a middle income area. According to their findings, more than 50 percent of residents believed the likelihood of violent crime was the greatest in public spaces. Furthermore, 36 percent and 34 percent of their respondents perceived informal settlements and parks to be the most unsafe areas, respectively. According to Perry *et al.* (2008), residents in Reservoir Hills regarded parks as unsafe areas because young troublemakers and criminals tended to congregate in those locations and thus also associated parks with alcohol, drugs and disorderly behaviour. Also in Durban, Pillay and Pahlad (2014) interviewed 200 houseolds in the South of Durban and found that men and women viewed parks in their community differently. Their results showed that about approximately 20 percent of men and 47 percent of women (from their group of respondents) perceived parks as unsafe. Consequently, their research also found that more men visit their local green spaces than women. The researchers postulate that the quality of these community green spaces influences these varying gender perceptions of safety and use. Finally, according to the Statistics South Africa's Victims of Crime Survey for 2014/15, residents (nationally) tended to avoid parks as they are seen as being unsafe and associated with crime (Statistics South Africa 2015).

Urban green space has also been found to be associated with crime both internationally and locally, where green spaces are known as public places such as “parks, gardens, greened thoroughfares, sporting fields, and ovals” (Kimpton, Corcoran and Wickes 2017:304). A recent study by Venter *et al.* (2022) found that overall green space throughout South Africa was linked to less violent and property crime, while having no influence on sexual crime. These researchers also found that there was more property crime but less violent crime with increased tree cover. Moreover, increased property crime was associated with increased proximity to parks in South Africa. The researchers conclude that their findings prove that greener communities, nationally, tend to be associated with less property and violent crime, however, they acknowledge that the quality, maintenance and distribution of these spaces play a significant role in this crime versus green space relationship. They highlight the work done by Groff and McCrod (2012) and Kimpton *et al.* (2017) which states that better maintained parks with good fencing, security and lighting are associated with lower crime rates than those that lack maintenance and fundamental amenities.

So, although green spaces are found to be associated with reduced crime, if the quality and maintenance of these spaces are not looked after, crime may be higher near or in green spaces. A local example is a study conducted by Mathenjwa (2017) who assessed the Khayelitsha Wetlands Park in Khayelitsha and found that although it was one of the better-quality parks across various townships in the City of Cape Town, it was still not as well maintained as other parks in more affluent areas. This study revealed that some community members associated this particular park with rotten smells originating from uncontrolled waste discharge (from users upstream) ending up in the park. Moreover, some members residing near this park in Khayelitsha mentioned that homeless people and gangsters were found to congregate in the park since the dense vegetation acted as a shield behind which they committed their illegal activities. The respondents in this study suggested a few improvements for the park including increased security measures to improve the park's safety as well as provide better quality amenities and build fencing to enclose the area. Since the Khayelitsha Wetlands Park was said to be one of the better parks in the adjacent low income areas, this creates the perception that the other surrounding parks are less well maintained and therefore could pose a risk on park safety. Therefore, ill maintained parks and their surrounding areas can still be seen as crime generators in the local context of Khayelitsha.

2.2.5 Schools

Schools have been found to provide favourable opportunities for crime and act as crime generators throughout various contexts (Kautt & Roncek 2007; Murray & Swatt 2013; Roncek & Faggiani 1985; Roncek & Lobosco 1983). Schools exist in nearly all communities and, unlike other facilities such as alcohol outlets, are not regulated. Individuals gather together near school grounds, before and after school operating times, often with little guardianship. This increases their risk of victimisation. Roman (2002) found that schools act as crime generators (associated with violent crime) in Prince George's County, Maryland, during school operating hours. The researcher also found that more deprived areas near schools were associated with more violent crime than less deprived areas.

Locally, Breetzke *et al.* (2021) found that sexual violence spatially clustered around primary and secondary schools in Khayelitsha while Masitsa (2011) noted that secondary schools have a similar 'criminogenic' effect across 44 townships throughout the Free State province. Both teachers and students were found to experience sexual assault and robberies during or after school hours. Masitsa (2011) also found that in some cases, the students themselves were the criminal offenders.

Finally, a study by Breetzke and Edelstein (2022) examined whether a number of facilities acted as crime generators in Khayelitsha. These researchers utilised intensity value analysis (IVA) to identify the level of intensity of crime (assault, robbery and rape) around schools, recreation hubs, transport interchanges and alcohol outlets. They found that schools, recreation hubs and transport interchanges act as crime generators in Khayelitsha, with schools having the greatest crime intensity in comparison to the other three facility types.

The above-mentioned studies highlight the importance of taking these so-called risky facilities into account when identifying safe walking routes in Khayelitsha. Importantly, these crime generators/attractors act within a specific spatial unit of analysis ranging from the macro-level (i.e., a school is present within a particular neighbourhood), to a micro-level (i.e., a school is present along a particular street). Understanding the importance of the unit of analysis being used is, therefore, vital in assessing crime risk, particularly for individuals navigating a particular transport route.

2.3 Street Segments as a Unit of Analysis

Researchers analyse crime at various level of aggregation ranging from coarse municipalities and neighbourhoods (Brantingham & Brantingham 1998; Braga & Weisburd 2010) to finer street blocks/street segments (de Melo *et al.* 2015; Chainey *et al.* 2019; Favarin 2018; Rice & Smith 2002; Umar *et al.* 2020; Weisburd, Groff & Yang 2012; Weisburd & White 2019; Wuschke *et al.* 2021). Weisburd *et al.* (2004) noted that larger units such as neighbourhoods have been most often used in traditional spatial crime research but noted that there has been a recent shift in modern spatial crime research to finer units of analysis such as street segments. Sparking this shift is the realisation that larger places such as neighbourhoods that are labelled as 'criminogenic' are not all or uniformly 'bad'. Indeed, there are some 'good' places within so-called 'bad' neighbourhoods. Consequently, only particular places within an entire neighbourhood may be responsible for the majority of the crime occurring in a neighbourhood.

This, in part, explains why micro-places such as street segments are becoming an increasingly popular unit of analysis when undertaking spatial crime research (see de Melo *et al.* 2015; Hermann 2012; Umar *et al.* 2021; Weisburd *et al.* 2004). Weisburd *et al.* (2004) describes micro-places as being particular locations within larger geographic areas, such as street blocks, street segments or addresses. According to de Melo *et al.* (2015) this domain of research is termed 'micro-spatial unit of analysis' with street blocks now considered to be the most accurate unit of analysis in a variety of modern micro-spatial studies. Using street segments as a unit of analysis is also advantageous when attempting to understand spatial crime trends. According to Groff and Lockwood (2014) this is because street segments are a good estimator of behavioural settings (social structures formed between people and objects at a small scale) which in turn shape criminal tendencies. Similarly, Weisburd *et al.* (2004) describe street segments as 'city organizers' which provide a more precise assessment of crime risk than traditional larger units of analysis (also see Groff *et al.* 2010).

Indeed, street segments represent a unit of analysis that is not too large nor too small, circumventing the ecological fallacy problem (Curman *et al.* 2015; Weisburd & Amram 2014; Weisburd *et al.* 2004). Moreover, if units larger than street segments are utilised, important crime trends found at micro-places can be lost. Groff *et al.* (2010) indicates that the routine activity theory fundamentally occurs at the street segment level (micro-level). This is because the routine activity theory by definition only refers to micro-level concepts: the actual crime incident, the unit of analysis at which it takes place as well as the three elements (i.e., motivated offender, suitable target and lack of guardianship) that must converge at the time of the incident for the theory to hold true. This theory does not include any "constructs larger than individual actors (the offender, the victim, and the guardian), places, and moments in time are required or used" and can thus be thought of as being a strictly a micro-level theory (Eck 1995:784). It is true that some crimes may be linked across streets as an effect of bigger criminal operations, such as drug markets or housing projects that span across several streets (see Weisburd *et al.* 2004). Despite this limitation, street segments can provide more valuable information about the machinations of crime than studies done at coarser levels of aggregation.

Rather unsurprisingly, a plethora of studies have examined how crime varies spatially at the street segment level of aggregation (Curman *et al.* 2015; Favarin 2018; Groff & Lockwood 2014; Weisburd & Amram 2014; Weisburd *et al.* 2012). One of the first studies was undertaken by Sherman *et al.* (1989) in Minneapolis, Minnesota who analysed crime using addresses as a unit of analysis. The researchers discovered that only three percent of addresses accounted for 50 percent of crime. Similarly, Weisburd et al. (2004) found that roughly four percent of street segments in Seattle, Washington, accounted for 50 percent of crime in their study. Furthermore, the researchers noted that these figures remained relatively constant over a 14-year period (1989 – 2002). This, they suggested, is indicative of a temporal stability in crime concentration across street segments. Later Groff *et al.* (2010) conducted another street segment analysis in Seattle, over a 16-year period (1989 – 2004) and found that a large number of street segments exhibited no crime or experienced stable low crime over the study period. The researchers did, however, recognise that there were street segments within those areas that experienced lots of crime or increasing crime, confirming previous findings that crime concentrates at very specific places. The street segments with no (or low) crime were found to be dispersed across Seattle, including in some high crime neighbourhoods. The researchers concluded that crime patterns at street segment level are greatly influenced by the characteristics of those segments including the location of 'risky facilities' on certain streets. A later study conducted by Weisburd *et al.* (2012) investigated crime during the same 16-year period in Seattle and found between 4.7 and 6 percent of street segments were responsible for 50 percent of crime, and only one percent of street segments were responsible for 23 percent of crime. Across this 16-year period, the concentration of crime at place was stable.

Outside the United States, Curman *et al.* (2015) undertook a street segment analysis of crime in Vancouver, Canada, and found that the crime pattern results were very similar to studies in the United States, with 7.8 percent of street segments in Vancouver accounting for 50 percent of the crime. In Europe, Favarin (2018) undertook a street segment analysis of crime in Milan, Italy, during 2007 – 2013 and found that on average, across this seven-year period, four percent and 1.6 percent of street segments contained 50 percent of burglaries and robberies, respectively. In Tel Aviv-Jaffa, Israel Weisburd and Amram (2014) conducted a street segment analysis of crime and found that 4.5 percent of street segments in Tel Aviv-Jaffa accounted for 50 percent of crime. Strikingly, the researchers also identified that only 0.9 percent of street segments accounted for 25 percent of crime, indicating an intense concentration of crime at very particular places in Tel Aviv-Jaffa. It is important to mention, however, that the studies mentioned about most often have similar 'Western' urban spatialities and that the crime data utilised in both research studies occurred across similar years. It is therefore important to explore these theories in less developed contexts in order to confirm these crime trends.

Spatial criminology research is largely concentrated in North America and Europe with studies lacking elsewhere, especially in less developed contexts. de Melo *et al.* (2015) aimed to fill this research gap by investigating crime trends across space in Campinas, Brazil. The researchers examined whether crime trends closely resembled trends found in North America and elsewhere in the world. The researchers compared crime across three units of analysis ranging from macro-places (ponderation areas and census tracts) to micro-places (street segments) and found that results of crime analysis changed depending on the unit of analysis being employed. Focusing solely on street segments alone, they found that roughly four percent of street segments in Campinas were responsible for 50 percent of crime and found that roughly 29 percent of street segments accounted for 100 percent of crime in the area. This finding further illustrates the magnitude of crime concentration in this city, and a concentration which is much higher than most of the studies conducted in the United States. Extending research in the South American context, a more recent study by Chainey *et al.* (2019), examined the spatial concentration of crime across 37 cities in South America. The researchers found that 2.5 percent and 0.8 percent of street segments accounted for 50 percent and 25 percent of crime, respectively across all cities.

Very little research has been undertaken in Africa examining crime at the street segment level. One notable exception is Umar *et al.* (2021) who undertook a street segment analysis of crime in Kaduna, Nigeria. The researchers made use of three methods in order to collect their data. First, they conducted fieldwork in order to locate residential and other buildings in the study area. Second, the researchers gathered data about the built environment describing its condition by means of a Block Environmental Inventory (BEI)[2]. Finally, a 'place-based victimisation survey' was used to collect crime and demographic data from two urban districts within Kaduna. This survey was in the form of a structured questionnaire interview focusing on two crime types, namely, breaking and entering, and domestic theft. The survey data enabled the researchers to geocode the crime incidents. The researchers argued that African cities possess vastly different urban spatialities and street network patterns in comparison to North American and other 'Westernised' cities. This creates a distinctive environment for crime and it is for this reason, the researchers initially assumed that crime trends in Nigeria would differ greatly from previous studies. The researchers found that roughly 11 percent of all street segments accounted for 50 percent of all crime. The concentration of crime at the micro-level in this Nigerian context closely resembled the trends found in previous international research.

Another notable study was conducted by Theron *et al.* (2023) where crime concentration at the street segment level in Khayelitsha, South Africa, was analysed. In this previous research study, streets were split at intersections as well as into 50-metre segments in order to represent crime concentration most accurately at this micro geographical level. These researchers took a look at three crime types, namely, property, sexual and violent during a five-year period between 2012 and 2016. It was found that 49, 42 and 14 percent of street segments accounted for 100 percent of violent, property, and sexual crime, respectively. Moreover, merely three percent of street segments accounted for a quarter of violent crime while only two

[2] The environmental assessment of a street block regarding any physical "incivilities, territorial functioning and defensible space features" that act as potential crime catalysts. (Perkins, Meeks & Taylor 1992: 24)

and one percent of street segments in Khayelitsha accounted for a quarter of all property and sexual crime, respectively. When looking at all crime as a whole, only three percent of street segments were responsible for 25 percent of all crime.

Kim and Hipp (2018) argue that the underlying structure, accessibility and surroundings (including crime generators or attractors) of street networks can shape the patterning of crime at the street segment level. The researchers argue that increased accessibility of street networks can increase crime. In their study, they showed that street segments located near highways experienced 70 percent and 78 percent more aggravated assaults and motor vehicle thefts, respectively, than segments located further away from highways. Moreover, those street segments that are near highways experienced 108 percent more burglaries and 127 percent more larcenies than other street segments. Although not as severe as highways, street segments adjacent to parks also experienced more burglaries, motor vehicle thefts and larcenies, and aggravated assaults than segments not adjacent to parks. Street segments along city borders also experienced more aggravated assaults, robberies and larcenies, respectively.

Understanding *why* and *where* crime concentrates on a street network can greatly assist with the safe navigation *through* these networks. This is especially true for a township like Khayelitsha, with a unique geographical and socio-economic context. It is evident from the reviewed literature that crime tends to concentrate at the street segment level across many geographical contexts including Khayelitsha. Therefore, it is necessary to include crime statistics when determining the safest walking routes in this township context. Street segments with a higher concentration of crime should be avoided along a walking route to maximise pedestrian safety and minimise risk of crime along their journey. This could be done by assigning weights to each street segment in a network to indicate their relative crime risk. In turn, the safest route would ultimately minimise this crime risk. The next section dives into graph theory, network analysis concepts and how weights (crime risk indicators) can be applied in this way.

2.4 Graph Theory and Network Algorithms

Graph theory was founded by Euler (1735) when he discovered how one can travel through the town of Königsberg in such a way that each bridge, within the set of seven, is visited only once. By interpreting this problem as a collection of edges (bridges) and nodes, Euler formed the basis of what we now know as graphs. In graph theory a network is described as being a graph, $G=(V,E)$, composed of a collection of interlinked nodes (V) and edges (E). This provides the mathematical explanation behind these node-edge connections. The size (M) and order (N) of a graph is determined by the number of edges and nodes found within the network, respectively. Nodes are assigned unique labels (integers) such that when edges are formed between two linking nodes, the edges are labelled according to the respective node pairs (Davies & Johnson 2015). A graph is considered to be directed when the collection of edges connected by nodes are orientated, such that certain nodes are only related to other nodes in particular directions. A path is a collection of distinct nodes, and a sequence is a collection of nodes that are not distinct. Davies and Johnson (2015) describe a path as being a directed sequence, where nodes can be traversed by following the edges linking them. To illustrate this concept, a path will run through ten nodes (labelled 1 to 10) by linking each node consecutively, whereas a sequence will start and end at node 1 and 10, respectively, but can traverse intermediate nodes in any order.

In terms of graph theory, street networks also contain a collection of nodes (intersections) and edges (street segments linking intersections along which vehicles and pedestrians can travel). Street networks can either be referred to as topological (relational/nonspatial) graphs or spatial graphs. Topological distance refers to the number of street segments along a path (Goddard & Oellermann 2011) whereas spatial/metric distances refer to physical distance in metres or kilometres, for example (Crucitti, Latora & Porta 2006). Edges between nodes can also be assigned weights (Abudiab *et al.* 2004; Frith, Johnson & Fry 2017; Zhong *et al.* 2014). These weights act as external factors that impede the movement through a network and can include the cost of travel in terms of distance (Martínez Mori & Samaranayake 2019), time (Martínez Mori & Samaranayake 2019) or volume (Zhong *et al.* 2014) along a network.

In most prior literature, street networks are treated as spatial networks (Crucitti *et al.* 2006; He *et al.* 2019; Zhong *et al.* 2014). Martínez Mori and Samaranayake (2019) emphasise that the design and structure of street networks mould the way goods and services are distributed, which, in turn, affect everyday activities. According to graph theory, the degree of an intersection is represented by the number of street segments that converge into an intersection (Davies & Johnson 2015). In terms of travel, there are a number of algorithms that have been designed to decide the optimal paths (i.e., the most cost efficient) to travel (i.e., with the least weight). A key algorithm is the Dijkstra (1959) algorithm which computes the shortest path between an origin and destination nodes in a weighted graph. The algorithm traverses all nodes in a network in order to find the shortest path from the starting node. The Dijkstra algorithm is often used in numerous GIS applications, such as Esri's worldrenowned ArcMap and ArcGIS Pro software packages (Esri 2023) and is said to be stable and easily applied to network topology (Chen 2020).

Another notable network algorithm is the Chinese Postman problem, which was one of the first seminal network problems introduced and solved by Kwan Mei-Ko in 1962. This well-known problem describes the dilemma that all postmen encounter each day, which is to find the shortest route to travel across a neighbourhood, where they start and end at the post office. In network terms, this refers to the route that will start and end at the same node while minimising the cost (distance in this case) to traverse each connected edge *at least once* in the network (Minieka 1979). Therefore, the Chinese Postman tour includes each edge *at least* once whereas the Euler tour includes each edge exactly once (Edmonds & Johnson 1973). Unlike the Chinese Postman and Euler tours, the Hamilton algorithm (named after Sir William Rowan Hamilton who founded the Icosian Game using Icosian Calculus; see Hamilton (1856; 1858)) ensures that each node, as opposed to each edge, in a network is only traversed once (Abudiab *et al.* 2004; Martínez Mori & Samaranayake 2019). Another well-known algorithm is the Travelling Salesman Problem (TSP) which is an example of a Hamiltonian circuit. To illustrate this algorithm, a travelling salesperson wishes to travel from city-to-city (visiting each node, a city in this case, in a network only once and ending at the same node they started) via a route that has the smallest total cost (i.e., distance) to travel. This total cost is the summation of all separate costs, which are assigned to each edge along the route (Abudiab *et al.* 2004).

The cost of movement through a network can also be determined by the level of crime risk per edge (i.e. a street segment in the case of street networks). This crime risk can be represented by means of a crime risk index which indicates the numerical magnitude of 'danger' on that edge (street segment). These indices are uniquely designed to identify locations (i.e., street segments) that are at a higher risk of crime. Importantly, the designation of a street as being 'safe' to travel using a crime index is not new. For example, Pang *et al.* (2019) assigned a crime index that represented the level of safety of a street segment within smart cities that are safe for walking in the United States. The index was calculated based upon previous crime data and using Kernel Density Estimation (KDE). Once developed, the crime index represented the safety of each street segment and real-time camera footage was subsequently sent to end users via cellular infrastructure. Similarly, Puthige *et al.* (2021) modelled safe routes for users in New York. Street segments were assigned a danger value in order to deter users from travelling along dangerous routes. This index was calculated based on a crime score, accident score and path length (kilometres). The crime score represented the weighted severity of a crime with certain crime 'weighing' more than others; for example, rape was weighted far higher than theft. The accident score was estimated using a weighted sum of injured and killed pedestrians, cyclists and motorcyclists, respectively. Relatedly, Kim, Cha and Sandholm (2014) designed a risky score per street based on Twitter feed data in Chicago while Lisowska-Kierepka (2022) developed a criminal risk index per grid cell (unit of analysis for their spatial crime study) in Wrocław, Poland, which was calculated by dividing the length of streets containing crime by the total street lengths that fall within the respective grid cell. This method provided an estimation of the likelihood of crime occurrence in these streets based on historical crime data and can help law enforcement determine optimal safety procedures. By applying these network algorithms, the crime risk along a route can be estimated and used in route analyses. Section 2.5 discusses how safe routes can be determined through various approaches, network analyses and software.

2.5 Safe Routes and Related Work

Google Maps and *Apple Maps* are well-known navigation applications that provide users with alternative fastest routes between inputted starting and destination locations. These routes are displayed with their corresponding estimated travel times and updated traffic information. Transportation modes, including walking, driving, taking a train and flying, can be selected which influences the generated routes outlined by the applications. The creators of another popular navigation application, namely *Waze*, saw a gap in these applications and designed a navigation application that also incorporates real-time (user inputted) locations of police blocks and dangerous road conditions. These applications, however, fail to consider other preferences that a traveller may have besides travel time and distance (de Souza *et al.* 2019; Galbrun, Pelechrinis & Terzi 2016; Sarraf & McGuire 2020). Indeed, different travellers will have different preferences, for instance, tourists may prefer scenic routes (Amirgholy *et al.* 2017; Chen *et al.* 2021), female university students may prefer safer routes home after an evening class (Badiora 2017; Ceccato & Loukaitou-Sideris 2022), city cyclists may prefer safer routes with dedicated bicycle lanes (Lusk *et al.* 2019), motorcyclists may prefer tarred, smooth routes instead of gravel routes (Sarraf & McGuire 2020), among numerous others. A study by Chen *et al.* (2021) considered three preferences in their path planning system, namely beauty (scenic views), safety (risk of crime) and happiness (aesthetically pleasing). In their research, they prioritised the traveller preference (i.e. either the beauty, safety or happiness) while ensuring the suggested route minimises the cost of travel, which in this case refers to the user-defined travel time threshold. In this way, the navigation solution was designed to suit more than one user requirement. Similarly, Amirgholy *et al.* (2017) conducted a stated preference survey and found that on the weekends, users considered street safety the most important aspect (above travel time) when selecting a route to travel.

There is an urgent need for navigation methods and systems that provide users with a safety risk assessment of alternative routes as opposed to simply the shortest or fastest routes. A considerable number of researchers have paid special attention to safety as the main travel preference in their analysis of safe travel paths (see Aljubayrin *et al.* 2017; Sarraf & McGuire 2020). For example, Sarraf and McGuire (2020) developed a Safe Route Planner navigation system which provides users with the safest route between an inputted starting and ending points in a street network that utilises past motor vehicle crash data as well as up-to-date data to provide a measure of 'safety' along those segments. Each street segment in the network is given a time weight (travel time in seconds) and a crash weight (a numeric value of one or more, where one represents zero crashes) which together (multiplied) forms an overall safety weight. The Safe Route Planner ignores street segments with high weights and returns the resultant shortest route (which is built on the Dijkstra algorithm (Dijkstra 1959), i.e. the shortest path algorithm). de Souza *et al.* (2019) designed a safe routing algorithm for vehicle rerouting called Better Safe Than Sorry (BSTS) using a street network (converted to a biograph), traffic congestion data, and crime data. The researchers used the Pareto-efficiency approach which aimed to improve both traffic congestion and crime risk in their re-routing algorithm. This re-routing approach limits traffic congestion spots by dispersing the traffic across multiple plausible routes. Consequently through their recommended routes, travel time was reduced for 80 percent of users and crime risk was reduced for 60 percent.

Therefore, proving that their algorithm can reduce both travel time as well as crime risk for individual users.

Another study by Shah *et al.* (2011) utilised crowdsourcing to develop a safe routing system called CROWDSAFE in Washington, DC. The researchers obtained crime data from crime reports written by individuals on the internet using their cell phones. The legitimacy of this crime data limits the success of this safe routing solution although the researchers did mention that if these unofficial crime records were used in conjunction with real police reports, CROWDSAFE would be much improved. Hossain *et al.* (2022: 71221) introduced an algorithm called the Safe Path for Everyone (SPaFE) where they focused on “user safety while commuting”. This algorithm was designed to solve the On-Road Risk Minimisation Problem (ORMP) based on historical multimodal and crowdsourced data. In their algorithm, they examined safety in terms of four attributes, namely, gender (since some routes are more dangerous for women than for men), severity (level of safety of an area or path), age (children and persons older than 65 years are seen as more vulnerable commuters) and time (daytime versus night-time). Each node (area) and edge (path) in the research conducted by Shah *et al.* (2011) was assigned a safety weight representing a combination of these four attributes. Zaoad, Mamun-Or-Rashid, and Khan (2023) took a step further by adding historical crime data as an additional safety attribute to the four existing attributes from SPaFE and considered gender, severity, age, time and crime type when assessing the safety of a route. In their system, named CrowdSPaFE, crime types were given corresponding weights based on the severity of the crime and their jail sentencing. It was found that both SPaFE and CrowdSPaFE successfully reduced the safety risk for commuters, however, CrowdSPaFE gathered more crowdsourced information and crime data making it more powerful.

Another safe route recommender method was design by Oh *et al.* (2017) who took time of day and day of the week into consideration. This method also considered historical crime events and facilities when determining safe routes. Each facility was assigned a crime risk value between one and ten (where one was the safest and ten was the most unsafe) based on five crime types that occurred at these places. Routes were subsequently assigned crime risks based on the facilities (and their corresponding crime risks) that were traversed along the way. Therefore, routes that traversed riskier facilities were deemed as more unsafe and had a higher likelihood of experiencing crime. Ultimately, when user selected start and end points, the system recommended the safest routes based on the facilities traversed, time of day and day of the week. Puthige *et al.* (2021) also created a safest route detection system that utilises a danger index calculated using historical crime data, and *k*-Means clustering. Their proposed solution aimed to provide end users with a warning regarding which routes are more dangerous than others, thereby giving them the opportunity to select their preferable route. The system does this by assigning street segments with a danger index which is a combined result of a crime score (weighted sum of crime events), an accident score (weighted sum of accidents) and the length (in kilometres) of a path. Routes with a lower total danger index are seen as safer and more preferrable.

Apart from the safest driving routes, past studies have also examined the safest walking paths in various contexts. For example, Galbrun *et al.* (2016) designed a safe urban navigation system, targeted at pedestrians, based on a street network dataset obtained from OpenStreetMap (OSM) as well as publicly accessible crime data (for Philadelphia and Chicago). The crime data was used to approximate the likelihood of a future crime occurring on any street segment. This street network was converted into an undirected graph whereby each edge (i.e., street segment) was assigned two corresponding weights, namely, length (physical length of the street segment) and crime risk (risk score representing the proportional chance of a crime occurring on the particular street segment). Their model aimed to find the shortest route with the lowest risk of crime between origin and destination points, where distance and crime risk were of equal importance. This 'SAFEPATHS' problem was therefore defined as a bi-objective shortest path problem.

Alfonso (2017) similarly developed a Safe Routes to School (SRTS) framework for two elementary schools in California using the Network Analyst extension in ArcGIS Pro. In their research, Alfonso (2017) showed how GIS can improve SRTS programmes by visualising the neighbouring areas around schools and assess their service areas. The researcher created a route analysis layer which comprised the street network, stops and various barriers (features that influence pedestrian safety along streets). It is important to note that these 'barriers' are a unique term introduced by Esri in the Route Analysis tool and refer to obstacles that impede movement throughout a street network. Street segments that intersect these 'barriers' are either avoided completely (when the barriers are set to be restrictions) or they are still traversed but at an added cost/impedance (when the barriers are set to be added costs or scaled costs). The researcher explained that if a scaled cost barrier has a value of one, then it does not add any further impedance on the intersecting street segment, however, if the value is less than or greater than one, then it has an influence on the 'cost' attached to the street segment. If a barrier had a scaled 'cost' of less than one, then the intersecting street segment was deemed safer than surrounding streets, however, if a barrier had a scaled 'cost' of more than one, then the intersecting street segment was deemed as more dangerous. The stops used in his study were the two Californian schools and non-random home addresses. The barriers, on the other hand, represented road intersections, walkways, freeways, crime hotspots (based on historical crime events) and areas that experienced pedestrian collisions in the past, which were in the form of point barriers, line barriers and polygon barriers, respectively. Each barrier was assigned a respective type and cost/weight. Crime hotspots and areas that experienced past pedestrian collisions were each assigned a scaled 'cost' of two with any street segment intersecting these polygon barriers subsequently regarded as more dangerous (twice as dangerous as other street segments due to the value of the scaled cost (i.e., two)) than a street segment that did not intersect one of these polygon barriers. Freeways were set as restriction line barriers to ensure pedestrian did not have to walk on these busy roads. Last, intersections that had cross guards present were assigned a scaled cost of 0.5 and walkways were assigned a scaled cost of 0.25, both barriers had a positive effect on the safety of the street segments that intersected the barriers. Consequently, the routes generated were considered safe given the environmental backcloth and underlying historical crime risk and were also short enough for students to walk with ease.

Finally, the City of Wauwatosa, Wisconsin, collaborated with an organisation known as Symbiont Science, Engineering and Construction, Incorporated, to design a safe routing application to support a Safe Routes to School programme (Eckdale-Dudley *et al.* 2018). The application was designed to assist parents in finding the safest walking routes to school for their children. Using ArcGIS Collector, Symbiont visited all street crossings across the city and recorded the corresponding safety characteristics (i.e., quality of paint markings, pedestrian signs and whether they were controlled or not). From this fieldwork, each street crossing was assigned a corresponding safety score. Heat maps of student homes were also generated to determine areas that required safe walking routes to nearby schools. Subsequently, the safest walking routes between student homes and nearby schools were determined by linking existing walkways to the safest street crossings (ones with the best safety scores), by making use of the Network Analyst extension in ArcGIS Pro Desktop. These routes were then published to ArcGIS Online so that it was easily accessible in an online application (built using ArcGIS Web AppBuilder) for parents and students. This online application provided widgets so that parents could search for the nearest safest walking route and to display subsequent directions.

Each of the aforementioned safe navigation methods/systems have, however, their limitations. First, they are all context-specific in terms of their urban spatial morphology as well as the respective crime and street network data used. Second, a number of studies are designed more for vehicle routing rather than pedestrian safety (de Souza *et al.* 2019; Sarraf & McGuire 2020), and finally, the vast majority of research has been undertaken in the United States with much less research been done in less developed contexts. This research study aimed to address some of these limitations by proposing safe walking route methods between two points in the unique township of Khayelitsha in the Western Cape province of South Africa. This is done using historical crime data from the South African Police Service and facility data from the City of Cape Town geospatial data portal and other data sources.

Chapter 3: Study Area

Khayelitsha is a township located on the urban periphery of Cape Town. In South Africa, a 'township' refers to a built-up residential area located on the periphery of former Whites-only urban areas. Under the apartheid policy focusing on separate development, these areas were originally reserved for non-White people only (i.e., Black African, Coloured and Indian population groups) although townships are still predominantly (>95,0%) inhabited by non-Whites. When they were established during the 1950s and 1960s they were never intended to grow into fully developed and independent communities with a complete infrastructure (e.g., shops, schools, community and recreational facilities, work places). They were seen as largely dormitory towns for mainly male migrant workers from the then 'Bantustans' or homelands[3]. Currently, most townships in South Africa still include a more stable, higher socio-economic (chiefly lower middle class) area inhabited by people who have lived there for a long period of time or whose parents/relatives had lived there since the establishment of the township. These older and more established areas may have developed features such as taverns, clubs, recreational facilities and churches, which have turned such areas into fully fledged communities although most often still lacking in basic infrastructure and services. However, adjacent to these areas lie more informal settlements and 'matchbox' developments that have sprang up since democracy in 1994. Although not intended, these differ little from the original dormitory towns. Writing about townships under apartheid, Chikane (1986) described them as typically characterised by widespread malnutrition, poor or non-existent health systems, ill-equipped and overcrowded schools, inadequate or non-existent social security, and high levels of unemployment.

[3] The term "Bantustan" refers to an apartheid regime policy which set about the creation of "independent" homelands for black South Africans.

Khayelitsha is the largest township in the Western Cape province of the country with a population of roughly 400,000 inhabitants, of which almost 99 percent are black African (Statistics South Africa 2011). It is one of last townships that was artificially 'created' in apartheid South Africa. The township was intended to house predominantly Xhosa-speaking black Africans and concomitantly provide a cheap form of migrant labour for the then former Whites-only neighbourhoods located in the central business district and surrounding neighbourhoods of Cape Town. Despite the arrival of democracy, Khayelitsha remains poor and socially and economically marginalised from Cape Town. Roughly 40 percent of residents of Khayelitsha are unemployed, with youth unemployment (aged 15-23) at over 50 percent (Statistics South Africa 2011).[4] Approximately 74 percent of households have a monthly income of R3,200 or less *(~US$200).* Notably, crime is of particular concern in Khayelitsha with the main policing precinct consistently among the most violent precincts in the country with contact crime[5] in particular almost double the national average (Crime Hub 2021)

Previous research in Khayelitsha has shown that crime concentrates spatially in the township (Breetzke & Edelstein 2019), as well as the fact that certain facilities such as schools and transport interchanges in Khayelitsha tend to generate crime (Breetzke & Edelstein 2022). Interestingly, access to certain facilities has also been found to influence crime resilience in the township (Pijper, Breetzke & Edelstein 2021). That is, neighbourhoods in the township have been found to be more resilient to crime when there is less access to schools, fire stations, police stations and

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[4] This is the most recent census undertaken for which data is available. The 2021 census was postponed due to the Covid-19 pandemic and is in the process of being conducted (July 2022).
[5] 'Contact crimes' refer to when a person or people are injured/harmed or threatened with injury/harm during the commission of a crime. A further sub-category of 'contact-related crime' is used for violent crimes committed against property with the intention of causing damage to a person, for example arson or malicious damage to property.

clinics. Khayelitsha lacks well-maintained infrastructure, such as roads and streetlights, which increases the risk of crime, and also leads to a general reluctance from the police to patrol certain areas, particularly the more informal areas. This lack of policing or inefficient policing, encourages local residents to turn to violence and vigilantism in order to control crime (Forgus *et al.* 2014). In terms of policing, Khayelitsha is served by three police precincts: Khayelitsha, Lingelethu-West and Harare (see Figure 1 below).

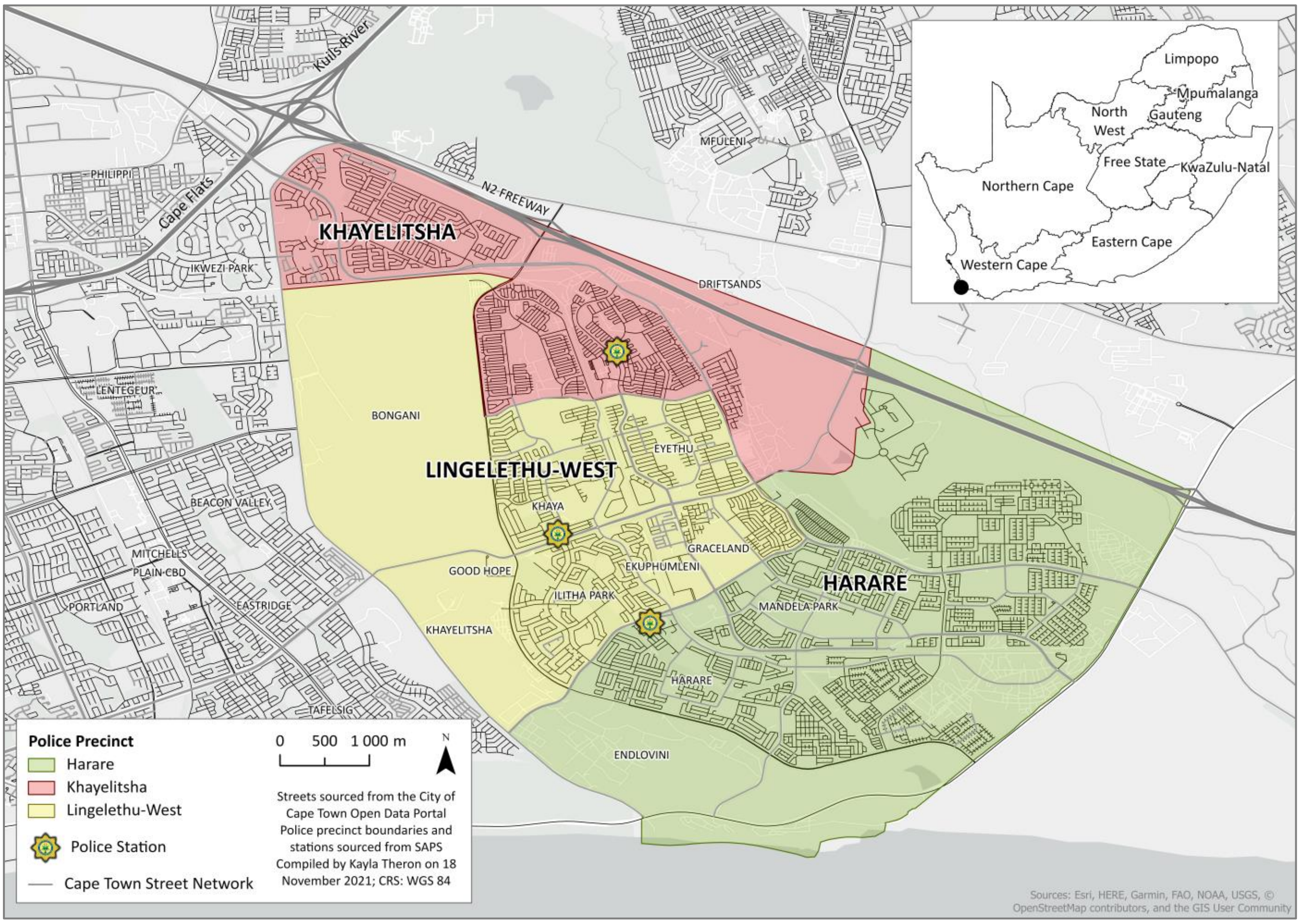

Figure 1: Greater Khayelitsha policing precincts

Chapter 4: Data and Methods

4.1 Data

This study utilised various types of spatial data, including street network data, crime, and police precinct data, and facility data.

- Street data

Road centreline data was obtained from the City of Cape Town Open Data Portal. This data consisted of line features that were segmented at every road intersection and were in Esri Shapefile (.shp) format. The data was originally published in February 2019 and updated in May 2021. This dataset was most appropriate for this research study because it was both topologically correct and comprehensive. Topology is a crucial consideration when deciding which dataset is best for street segment analysis. Spatial analysis of streets will be inaccurate if the underlying data is not topologically sound, due to errors and redundancy in calculating street lengths. The only exception is when a street dataset is used for visual purposes in a map, for example a study area map that includes streets to sufficiently orientate the map reader.

Only the formal street network in Khayelitsha was used in the study (informal streets and footpaths were excluded). The reason for this decision was that the outskirts of Khayelitsha contain many informal dwellings and numerous informal pathways (streets and footpaths) which were not included in the City of Cape Town street dataset. Consequently, the topology of these pathways was unknown, making it problematic to accurately map and undertake any spatial analysis. Figure 2 shows the road centreline data obtained from the City of Cape Town.

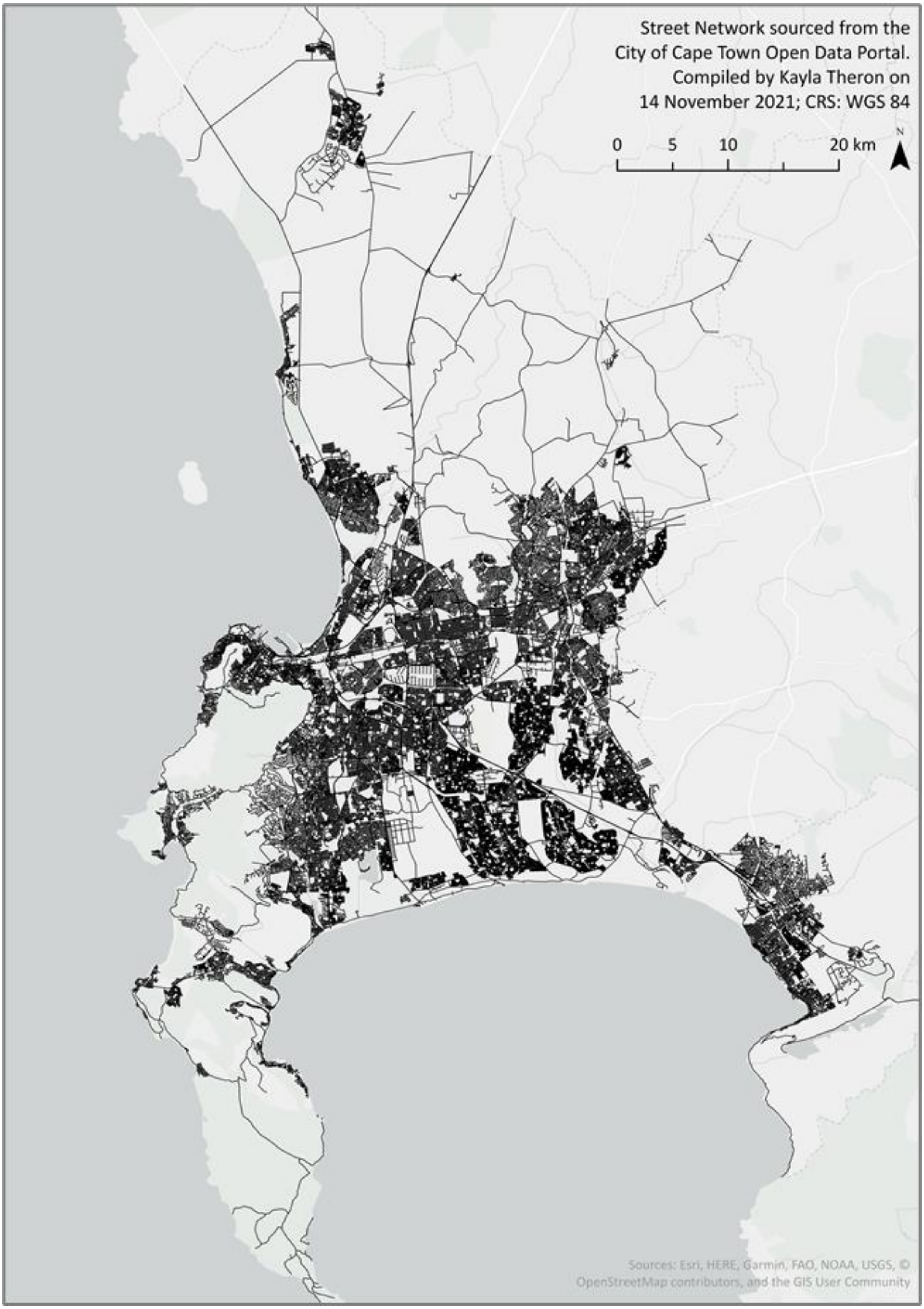

Figure 2: The City of Cape Town Metropolitan Municipality street network

A total of 107,466 street segments were obtained for the City of Cape Town with each segment containing 29 attributes, including road names, unique identifiers (ID), direction, surface type, speed limit in kilometres per hour, route number and segment length in metres. The attribute describing the segment length was the primary focus of this street segment analysis. On average, a street segment in the City of Cape Town is roughly 113 metres long. The shortest street segment is less than a metre and the longest is almost 14 kilometres while the standard deviation across the street network is approximately 208 metres. The median segment length is 72.5 metres, not being influenced by outliers. The streets within (and intersecting with) the Khayelitsha, Lingelethu-West and Harare police precinct boundaries were used as the study area (see Figure 3).

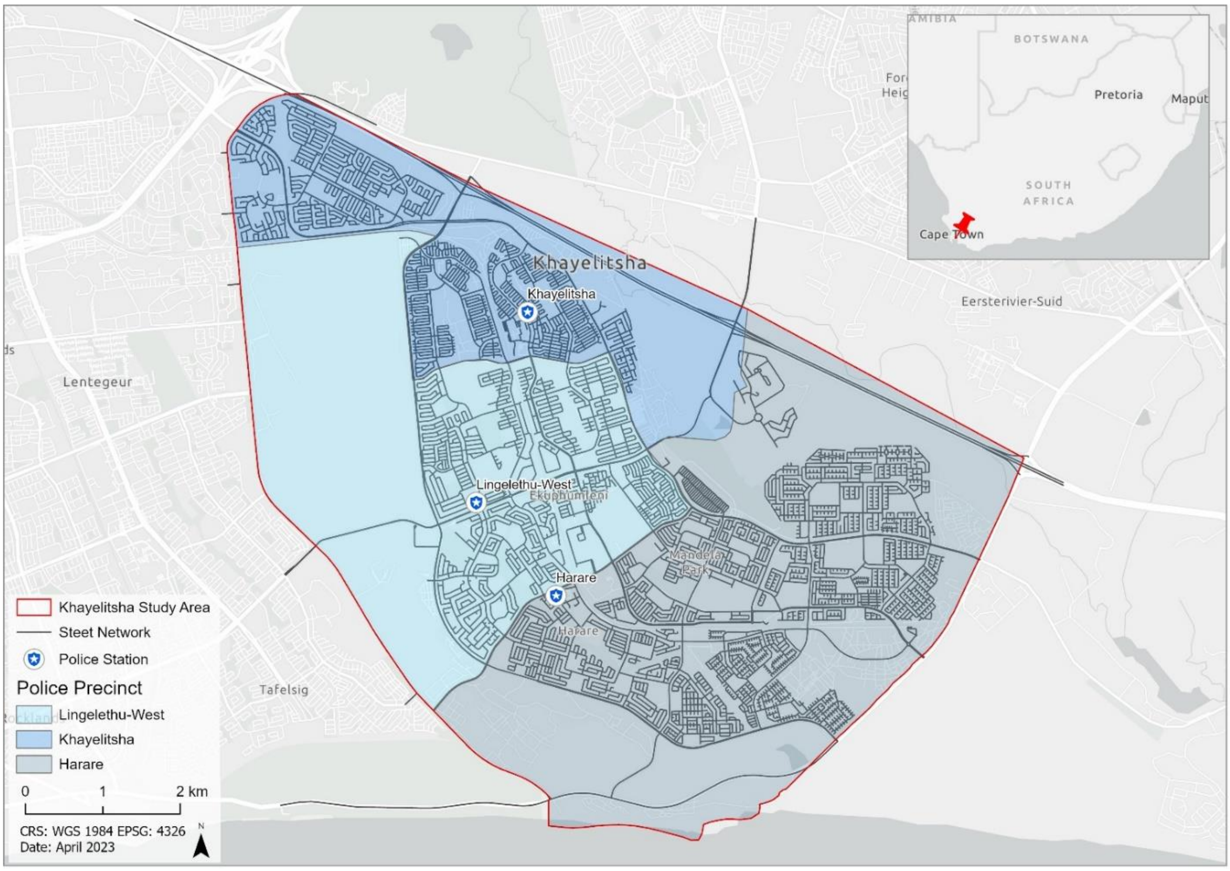

Figure 3: Street network within the Khayelitsha, Lingelethu-West and Harare police precinct boundaries

There were 6,089 street segments (split at intersections) within the Khayelitsha study area after clipping the road centreline data to the three police precincts. The shortest street segment in the Khayelitsha study area was roughly 2 metres while the longest street segment was approximately 3.5 kilometres, with a standard deviation of approximately 176 metres. This street network dataset was used in this current study to determine the safest walking routes in Khayelitsha.

- Crime data

The crime data used in this research study was obtained from the South African Police Service (SAPS) in point shapefile format (.shp). A total of 65,408 point crime incidents were reported over an eleven-year period (2006 to 2016) for the Khayelitsha, Lingelethu-West and Harare policing precincts. There are eleven attributes attained per crime incident including the incident unique identifier (ID), geographical location (X and Y coordinates), and crime type (offence). These datasets also indicate the year, month, day (and whether it was a weekday or weekend (Saturday/Sunday), and time (hour and minute) at which the incident occurred.

All crime incidents that occurred from 2012 to 2016 was used in this study as these dates are the five closest years to the year in which the street network data was sourced from the City of Cape Town. All crime types[i] (see end note at the end of the report for the full list of crime types) were included in the analysis such as rape, sexual and indecent assault, house, bank, and business robbery, as well as common robbery with or without firearms, murder, attempted murder and common assault. The decision was made to include all crime types in this research study in order to improve the statistical power of the spatial analysis as well as the fact that it is assumed that most crime, regardless of the offence type, poses a threat to pedestrian safety. It is noted, however, that some types of crime may be more visible and relevant to pedestrians navigating a street network, than others. As a result, there were a total of 29,790 crime incidents that occurred between 2012 and 2016 within the study area. This resultant crime dataset was used in the analysis.

- Facilities data

Facilities data used in this study included shopping malls, transportation interchanges (bus stops and railway stations in this case), alcohol outlets, schools and parks. These facilities have previously been found to act as crime generators/attractors in local and international studies (see Badiora *et al.* 2015; Brantingham & Brantingham 1995; Breetzke & Edelstein 2022; Breetzke *et al.* 2021; Britt *et al*. 2005; Button 2008; Cameron 2022; Conrow *et al.* 2015; Franklin *et al.* 2010; Groff & McCord 2012; Jennings *et al.* 2014; Lutchminarain 2012; Loukaitou-Sideris 2004; Masitsa 2011; Murray & Swatt 2013; Natarajan *et al.* 2015; Roman 2002; Stucky & Smith 2017; Zhu *et al.* 2004). In total, 341 facilities were used in this study.

  - Shopping malls

There are four main shopping malls in Khayelitsha including Khayelitsha Mall, Nonkqubela Link Mall, Site C Plaza and Thembokwezi Square. The location of each mall was obtained and geocoded using Google Maps, and then validated using Google Satellite Imagery. This dataset was compiled in a Comma-Separated Values (CSV) file format which was then converted to a point shapefile (.shp) for further spatial analysis.

- Transportation interchanges

Bus stops were acquired from the City of Cape Town Open Data Portal. There were exactly 1,810 bus stops in total in the city, of which only 38 fell within the study area. A further dataset representing transport points (including airports, bus stops, helipads, railway halts, train stations, taxi stops and tram stops) was sourced from Open Street Map (OSM) which contained 5,004 features spanning across the country with a corresponding OSM ID, code, feature class and name[6]. Of this dataset, five railways stations (namely, the Kuyasa, Nonkqubela, Khayelitsha, Nolungile and Chris Hani stations) were located in the Khayelitsha study area. Both the bus stop and railway station datasets were in point shapefile format (.shp).

- Alcohol outlets

A list of officially licensed alcohol outlets was acquired from the Western Cape Government Liquor License Authority. The document obtained from the Authority listed each outlet in the province with a corresponding suburb, license number, license type, license holder, premises name and premises address. From this list, outlets with physical addresses located in the Khayelitsha study area were extracted. Each premises address was then geocoded (assigned a latitude and longitude) and validated using Google Maps and Google Satellite Imagery. This CSV file was then converted to a point shapefile (.shp) consisting of 138 liquor outlets in Khayelitsha. It is readily noted that previous research has mapped an alarmingly higher number of illegal alcohol outlets in Khayelitsha (see Matzopolous *et al.* 2017), however, despite

[6] It is important to note that taxi stops were not included in this research study although it is acknowledged that these may play a critical role in a developing context, such as Khayelitsha. The OSM dataset used in this research did not include taxi stops located in the Khayelitsha study area. An alternative comprehensive dataset representing these taxi stops was not available and therefore could not be included in the analysis.

numerous attempts at reaching out to these colleagues to collaborate, it was ultimately unsuccessful and only the official licensed data was used.

- Schools

An Excel spreadsheet containing the location (coordinates) and names of 98 schools in Khayelitsha was obtained from the Western Cape Department of Education. From these coordinates, a point shapefile (.shp) was created to represent the spatial location of these schools in the study area.

- Parks

Spatial data representing parks was obtained from the City of Cape Town Open Data Portal. The data was in polygon shapefile format (.shp) and included just under 6,000 parks with seven corresponding attributes (including name, sub area, park type, park name, access address, play equipment, area and length). Of this dataset, only 62 district parks and community parks were located within Khayelitsha. These were extracted and used in the study. Figure 4 shows the location of the street network as well as the six different types of facilities used in the study.

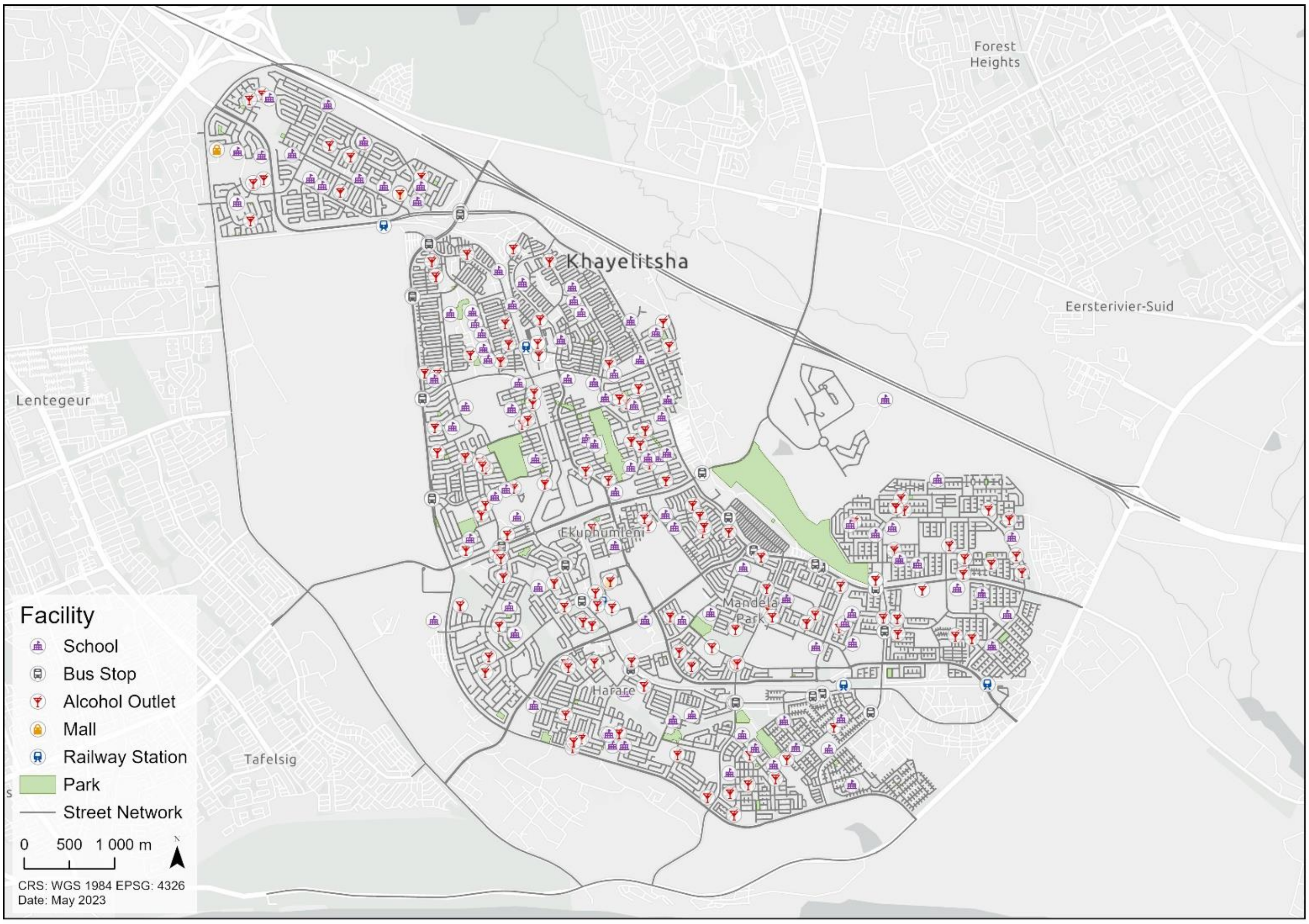

Figure 4: Map showing the risky facilities used in the route analysis

There are a few limitations to these datasets that are important to highlight. First, the crime data obtained from the SAPS might not be an accurate representation of true location, magnitude and nature of crime occurring in Khayelitsha. This is largely due to crime underreporting. Some victims or witnesses may feel too threatened or unwilling to report a crime.

Second, the metadata, such as the location, time, day or description of the offence, corresponding to the reported crime incidents may also be inaccurate. For example, the coordinates of a crime incident may have been recorded as the police station's location rather than the true location of the incident. The exact time or day of the crime incident could have also been incorrectly recorded as the time at which, or day on which, the crime was reported rather than the actual time at which the event occurred. Work by Edelstein and Arnott (2019) highlight some inaccuracies they found with regards to the location of some crime incidents in Khayelitsha. For example, some crime points (roughly 10 percent of crime points between 2010 and 2015) are geolocated incorrectly in a grid-like fashion while other crime points are recorded at the police station itself rather than the actual location at which the event took place. They emphasise that these inaccuracies may lead to false crime hot spots being identified and therefore the SAPS crime data may be seen as unreliable. They encouraged SAPS to implement more efficient data collection strategies by detailing exactly how a crime incident is recorded and listing any limitations thereof. This will ensure more reliable data capture.

Third, the positional accuracy of the risky facilities (n = 341) used in the route analyses is dependent on the respective data sources and location on Google Earth. It is acknowledged that some of the facilities may have been more built more recently and therefore existed after some of the historical crime events (i.e., some may have existed after 2016 when the last crime incident was recorded). This relates to the fourth limitation, which is the recency of the data used. The crime data in this research study represented historical crime incidents that occurred between 2012 and 2016 in the township. This meant that all crime risk measures in this study were based on historical data rather than up-to-date crime incidents (over the past five years). The street network used in this research was also only last updated in May 2021, making it outdated by roughly two years. This alludes to the possibility that some street segments could have been recently digitised and therefore not included in the dataset. Moreover, the street network and risky facilities data are more recently recorded than the crime data. Therefore, there is a chance that some of the street segments or risky facilities were not yet built/established at the time of some crime incidents.

Last, the completeness and true geospatial accuracy of the street network is dependent on the data source and the level of accuracy used when digitising the respective streets. For example, foot paths and other informal paths were not included in this street network dataset.

4.2 Analysis

Three alternative methods were proposed to determine the safest walking route between any two points in Khayelitsha. Method 1 involved determining the safest walking route between two points based on historical crime incidents only. Separate routes were calculated for all crime, as well as for daytime crime, night-time crime, weekday crime and weekend crime. Method 2 involved determining the safest walking route between two points considering the location of various crime generators/attractors (i.e., 'risky facilities' that are known to be associated with crime). Method 2 demonstrates an approach to finding the safest route between points when no crime data is available. Method 3 was similar to Method 2, however, in this case the historical crime data was used to weight the 'risky facilities' used in the route analysis. Therefore, Method 3 is most suitable when both crime and facility data is available, and when one would like to examine the individual risk each facility poses on a walking route. Each method involved a route analysis in a novel context (Khayelitsha) undertaken using the Route Analysis tool from the Network Analyst extension in ArcGIS Pro. Each method is described in more detail below.

Method 1: The safest walking route based on historical crime data

Method 1 aimed to find the safest walking route along the Khayelitsha street network between an origin and destination point location based on the underlying historical crime data. A route was deemed to be the safest if it encountered the lowest number of total historical crime incidents along the way (i.e., the lowest total crime per metre). This method was applied separately for historical crime data by day, night, weekend and weekday. The first phase of this method was to associate crime incidents (all crimes that occurred during 2012 to 2016) with street segments in order to calculate the crime count per street segment in Khayelitsha. In the initial analysis, a number of crimes were found to be located in open and/or vacant land at a far distance away from a street segment. It is unlikely in such instances that these crimes were spatially 'associated' with that (or any) street segment. In order to address this concern a 50-metre buffer was created around all streets and only crime incidents that occurred within this 50-metre buffer from a street was included in the analysis. This distance approximates a cadastral block in Khayelitsha. As a result, there were 26,109 (roughly 87 percent) crime incidents across all crime types that occurred within 50 metres of a street segment in Khayelitsha during 2012 to 2016.

The next step was to snap each crime incident to the nearest street segment. Note that crime incidents were only associated with one corresponding street segment, not multiple street segments, i.e., a single crime incident was only snapped to the nearest street segment ensuring that segments do not share the same crime incidents. After snapping crime incidents to the nearest street segment, the crime data and street data were joined based on a common street segment ID. A spatial layer comprising street segments and their corresponding crime counts was subsequently generated.

Later, crimes were disaggregated into day, night, weekday and weekend crime. Daytime was anytime between 6:00 in the morning until 18:00 in the evening, whereas night-time was between 18:00 in the evening and 6:00 in the morning. Weekdays were Monday to Friday and weekends were Saturday and Sunday. As a result, a separate route was calculated based on *all* historical crime, as well as for various temporal resolutions such as day and night-time crime, as well as for weekday and weekend crime calculated per street segment.

It is important to note, however, that since the individual street segments in Khayelitsha had varying lengths (shortest of almost 2 metres and longest of 3.5 kilometres), crime counts were not representative of actual crime intensity at this micro-spatial level. That is because longer street segments will most likely experience more crime merely because of their length. Therefore, in order to keep crime intensity on street segments comparable, these crime counts were divided by the geodesic length (in metres) of the corresponding street segment that the crime was associated with. Subsequently, each street segment had a relative crime count per metre (including crime per metre for day, night, weekday, and weekend).

The next step was to perform the route analysis using the Network Analyst toolbox in ArcGIS Pro. In particular, the Route Analysis tool was used to find the safest route between two points, i.e. an origin and destination. In order to conduct the route analysis in ArcGIS Pro, it was first necessary to prepare a topological network dataset that represented the street network on which the routing was applied. In particular, the street segments that were now assigned corresponding crime counts per metre, was used as the input for the street network dataset.

The Network Analyst tool in ArcGIS Pro provides an option for travel modes such as driving or walking, as well as travel costs associated with traversing a street such as distance or time. Consequently, a travel mode and travel costs were set for the Khayelitsha street network dataset respectively. In this case, *crime per metre* was the ‘impedance’ or cost of travel since the route with the least total historical crime was considered the safest. In other words, the ArcGIS Pro tool summed all corresponding crime count per metre values along the route between an origin and destination point and the route with the lowest overall value returned the safest route. The tool aimed to find the most optimal (safest, in this case) route based on a particular cost of travel specified (i.e., historical crime risk, in this case). Since the street segments were already assigned crime counts per metre, these attributes were selected to be the costs of travel. For example, if one wanted to try find the safest route during the daytime, then the daytime crime per metre would have been the cost of travel. Therefore in this example, the route between the origin and destination points consisting of the least overall historical daytime crime per metre, would be the safest. With regards to the travel mode, the travel type was set to *walking*. Along with crime per metre, the segment lengths (geodesic length in metres) were also assigned as a distance impedance/cost of travel.

To demonstrates how the Route Analysis tool operates, Figure 5 below shows the safest route between a random origin and destination point based on the underlying historical crime counts per metre per street segment.

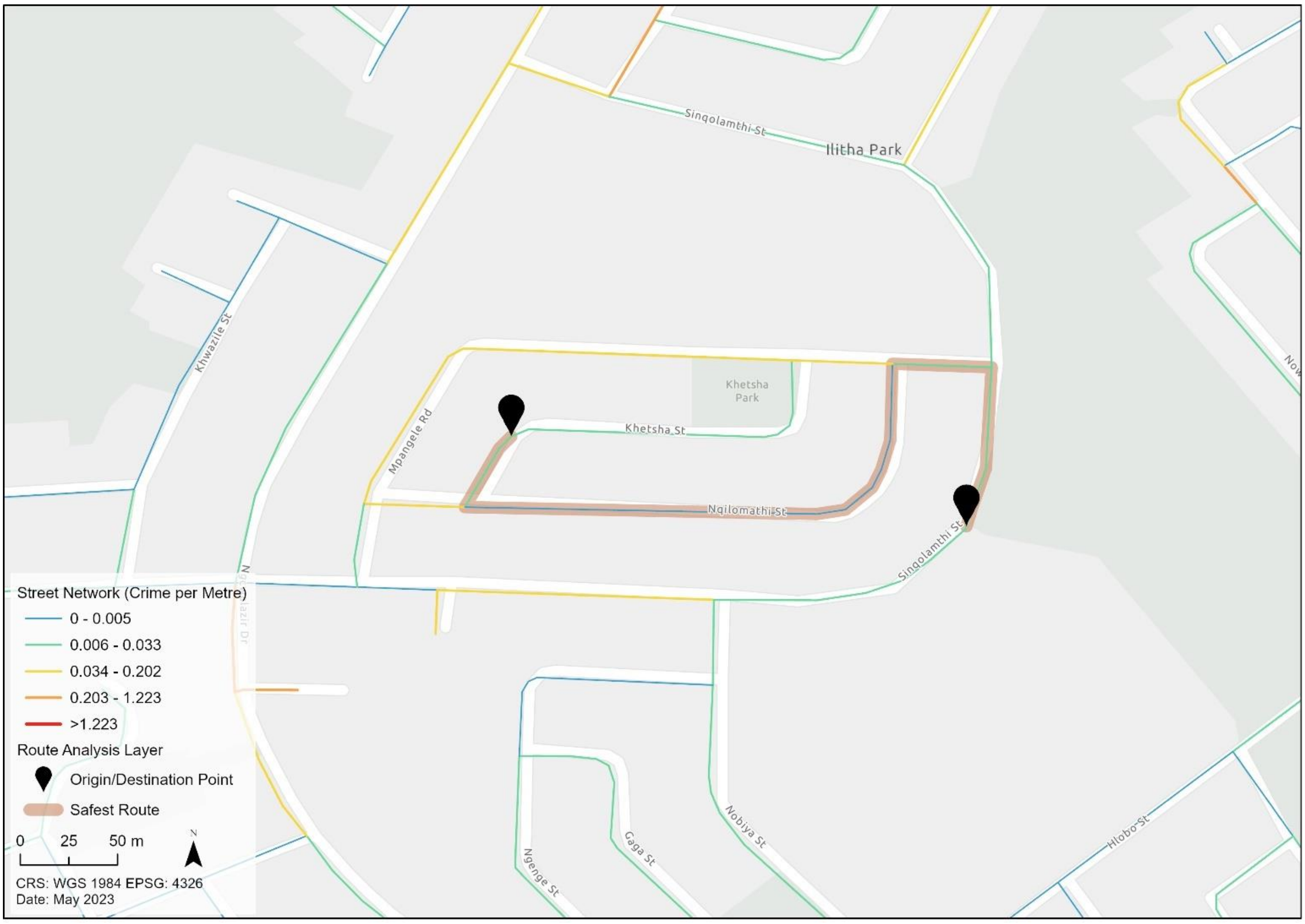

Figure 5: Map illustrating an example of how the Route Analysis tool operates

As shown in Figure 5 the suggested safest route (shown in brown) between the two points traverses street segments that have less historical crime (shown in blue and green) than adjacent street segments. The alternative routes would have been longer and would have encountered more crime per metre (yellow neighbouring street segments). This explains why this route (in brown) was the safest to walk between the two point locations shown on the map.

Before conducting the route analysis for this study, it was also necessary to establish origin and destination locations between which the route had to be calculated. In this study, the two locations (shown in Figure 6 below) were purposively selected so that the route ran through majority of the township. These points represent two hypothetical user-inputted locations within Khayelitsha, one being in the northern part and one in the southern part of the township. For consistency, these origin and destination point locations were used for all route analyses in this study (i.e., used in Method 1, Method 2 and Method 3).

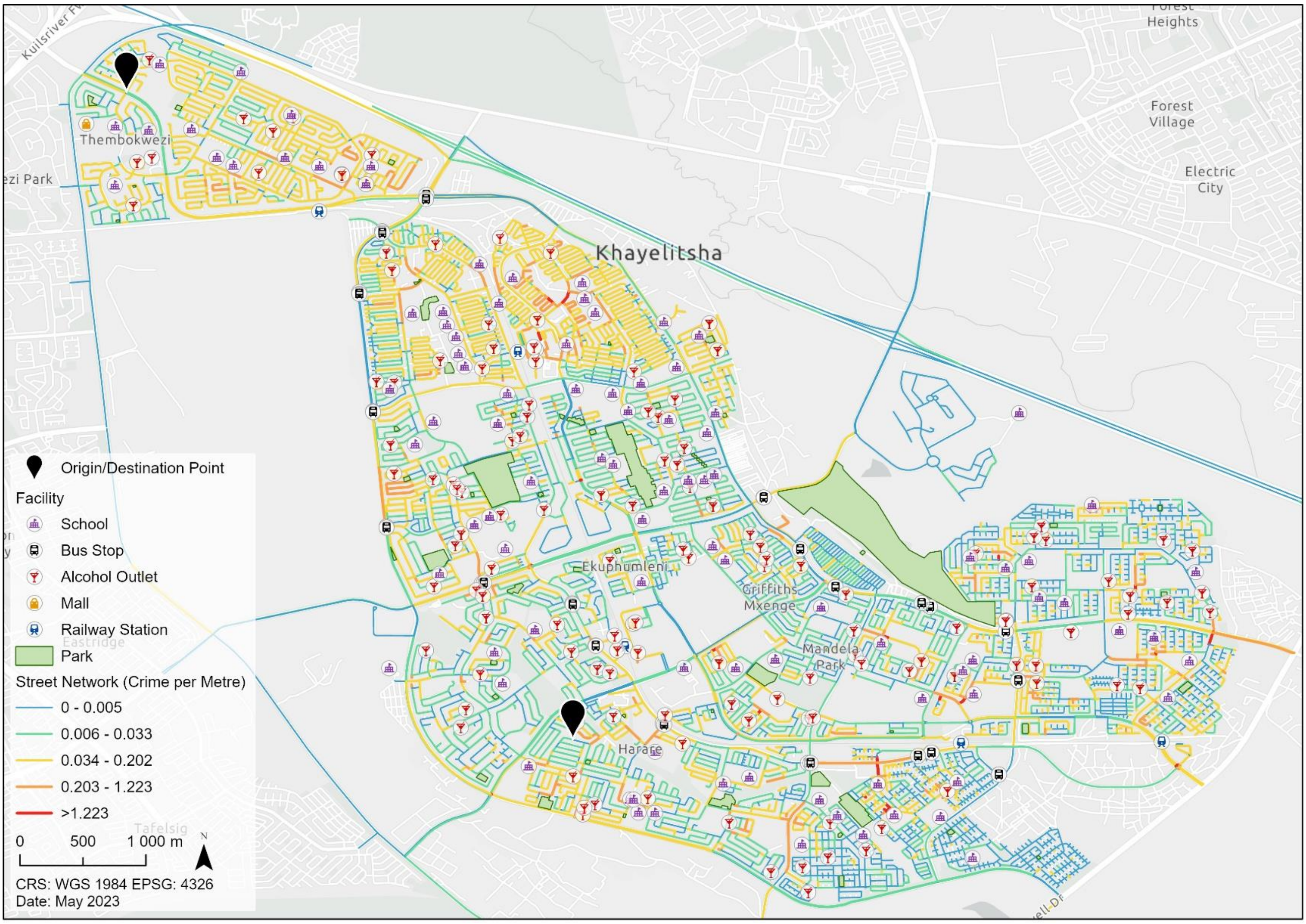

Figure 6: Map showing the origin and destination point locations used in each route analyses method

Initially, the shortest route between the origin and destination point was determined without taking any crime into consideration (see Figure 7 below). This was done to later compare it to the safest routes calculated throughout the study. Accordingly, the cost of travel was set to the street segment length (metres) and as a result the *shortest* route between the origin and destination points was acquired.

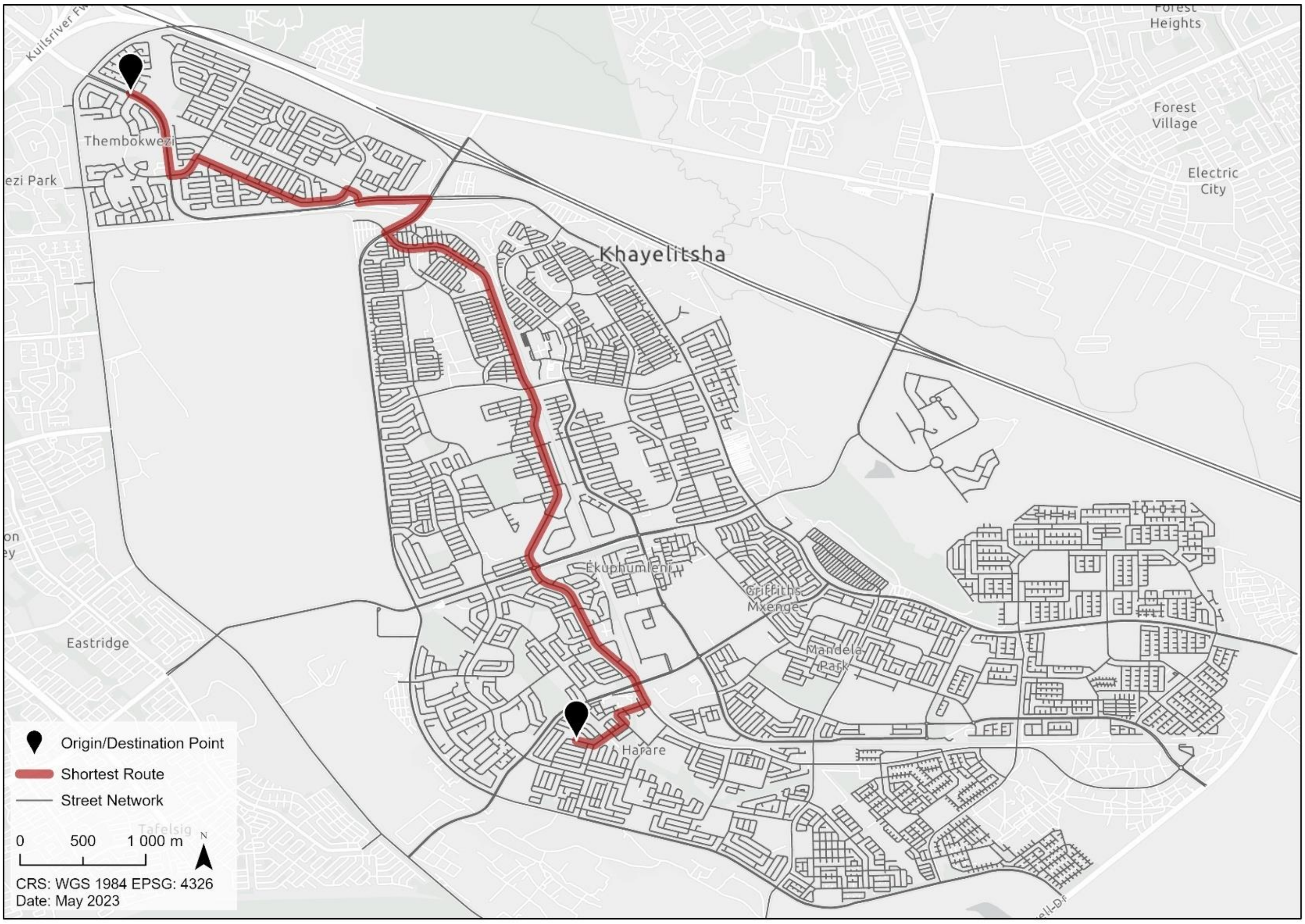

Figure 7: Map showing the shortest route between the origin and destination point locations

Thereafter, the cost of travel was rather set to total crime per metre to find the *safest* route. It was expected that the initial shortest route would have a much larger crime count than the safest route, and similarly that the safest route to have a much longer distance to travel than the shortest route. This is because the cost of travel was assigned to the attribute of interest: either segment length (for the shortest route) or total crime per metre (for the safest route). This method demonstrated two varying travel preferences that pedestrians may have when walking from an origin to destination point, that is, either distance or safety. The cost of travel was then also set to crime per metre for day, night, weekend and weekday, to find the safest routes based on these specifications and times.

Method 2: The safest walking route based on 'risky facilities'

This method involved determining the safest walking route between the same origin and destination point (outlined in Method 1) but in this instance the location of risky facilities in Khayelitsha were considered instead of the historical crime incidents. This method ultimately finds the shortest route with the least exposure to risky facilities along the way. Method 2 demonstrates an alternative approach to finding the safest walking route between two points when there is no crime data available and only data for risky facilities is accessible.

Based on the crime pattern theory, certain types of facilities may act as crime generators or attractors and may be perceived as being dangerous 'zones' (see Brantingham & Brantingham 1991). Pedestrians may therefore wish to avoid these zones. In this study, shopping malls, bus stops, railway stations, alcohol outlets, schools and parks were perceived as being so-called 'risky facilities. A 50-metre buffer was generated around each of these facilities where these buffer areas were perceived as being dangerous zones. It is difficult to empirically identify the distance at which the 'criminogenic' effect of these facilities dissipates. Ultimately, it was decided that since 50 metres approximates a cadastral block in Khayelitsha, that this distance was sufficiently big enough, all things considered. Any street segment that intersected these buffer areas were perceived as being within dangerous zones.

Th Route Analysis tool in ArcGIS Pro labelled these so-called dangerous zones as *barriers* since they act as obstructions and essentially hinder the traversing of certain street segments that pass through these dangerous areas. In this study, these barriers essentially altered and hindered the safety of a street segment. A route that passed through *barriers* was therefore considered more unsafe (than streets that did not intersect the barriers) due to it being exposed to these risky facilities. Consequently, the number of *barriers* that a route encountered impacted the overall cost of travel (safety) of that route, i.e., the more barriers traversed, the more unsafe a route was.

Importantly, these barriers could either be at a *restriction* or a *scaled cost*. A barrier was a *restriction* if it had to be avoided *completely* when choosing a route to travel. On the other hand, a barrier was a *scaled cost* if it merely altered the cost of travel by a certain amount when being traversed. To illustrate this, if a pedestrian strictly wished to avoid any alcohol outlets on their route, for example, then the alcohol outlet buffer zones would have been regarded as *restriction barriers* so that any street segments that passed through these zones would have been avoided completely. This means that the route could have been any distance, as long as it avoided the alcohol outlets entirely. Conversely, if a pedestrian merely regarded street segments near alcohol outlets as being less safe but was not willing to travel great lengths to avoid it completely, then these alcohol outlets would have simply been set as *scaled cost barriers*. This meant that these barriers only further impeded the cost of travel (by a positive scaled value) on the street segments that it intersected with.

If a *scaled cost barrier* was assigned a value equal to one, it meant that the barrier had no added influence on the cost of travel. A scaled cost value greater than one meant that the street segment that intersected the barrier would have been traversed at a greater cost, for example, it might have taken longer to traverse if time was set as the cost of movement. On the other hand, a scaled cost value less than one meant that the street segment that intersected the barrier would have been traversed at a lower cost, for example, it might have taken quicker to traverse if time was set as the cost of movement. According to Esri (2023:1) this type of barrier “scales the cost of underlying edges by multiplying them by the value of the Attr_[Cost] property” and “if edges are partially covered by the barrier, the cost is apportioned and multiplied”. For instance, if a *barrier* had a scaled cost of two (and distance was the cost of travel) it would have taken twice as long to traverse the street segments that intersected with that barrier due to the added influence. Therefore, with *scaled cost barriers*, resultant routes would have still included street segments that intersected with danger zones, however just at an added cost of travel.

For example, in Figure 8 alcohol outlets and parks were randomly assigned scaled costs of two and three, respectively, indicating their *hypothetical* relative influence on street safety. The safest route, indicated in brown in this example, avoided the park barrier and took a different route through the alcohol outlet barrier instead. This is because parks had a higher hypothetical scaled cost than alcohol outlets, i.e. they were regarded as more *dangerous*. This also explains how the Route Analysis tool does not necessarily avoid these barriers completely and still traverses them but at an added cost. The tool aims to traverse barriers that have lower scaled cost values associated with them.

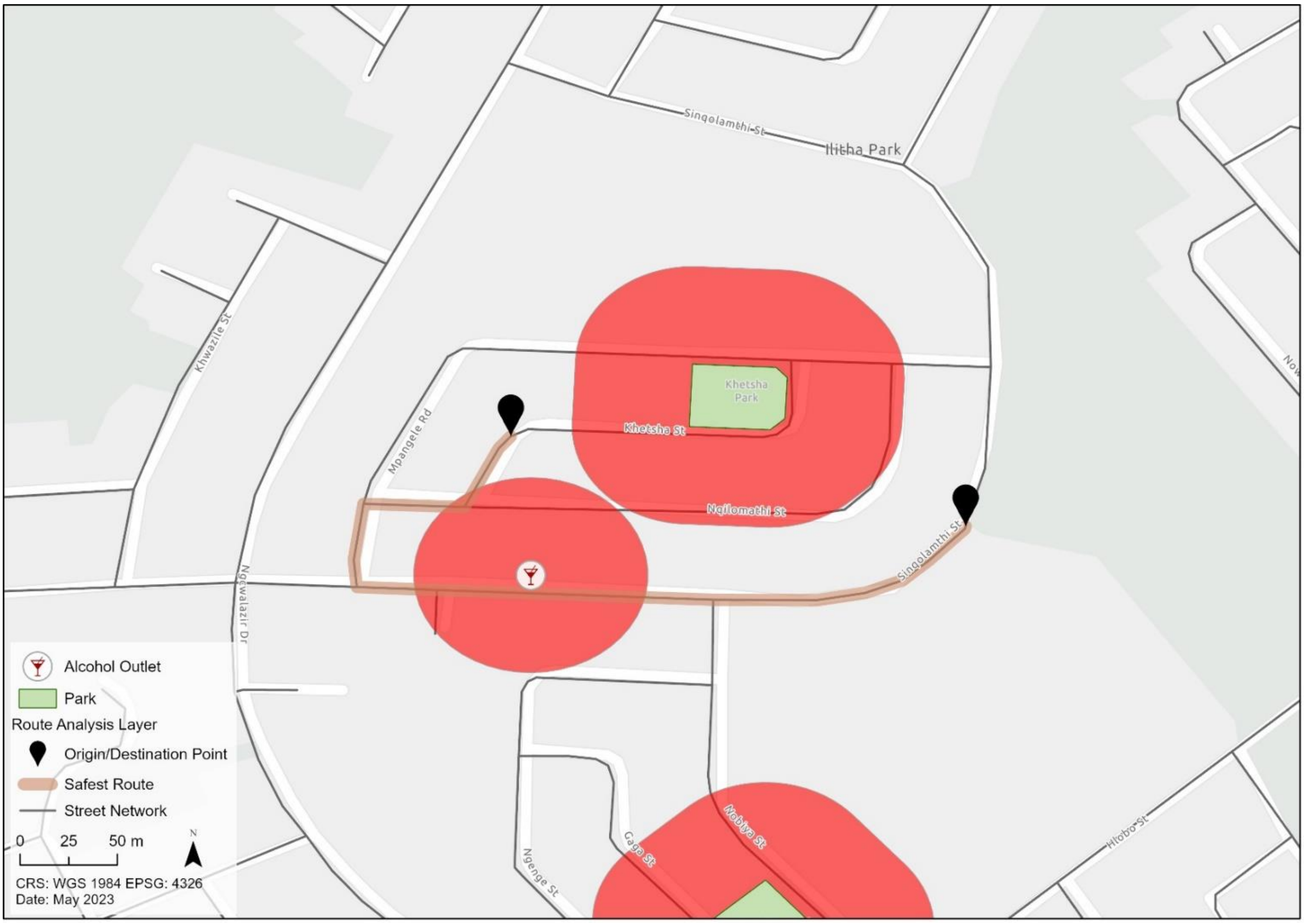

Figure 8: Map illustrating an example of the polygon barriers are used in the Route Analysis tool

Both *line* and *polygon barriers* were included in this study. Freeways and offramps were considered *restrictive line barriers*, forcing all possible routes to completely avoid these street types. This restriction ensured that pedestrians were never required to walk on freeways in order to get to their destination. This restriction was included due to the fact that freeways are dangerous for pedestrians, although it is known that residents do frequently walk on freeways in South Africa. As previously mentioned, the polygon barriers in this analysis represented the 50-metre buffers around each so-called risky facility and any street segment within these 50-metre buffers were considered to be within ‘dangerous zones’. Therefore, these polygon barriers signified danger zones. Instead of treating these danger zones as restrictions, they were set as *scaled costs*. That meant that the cost of travel increased by a certain scaled value if a street segment intersected these danger zones.

Another important thing to remember is that when barriers overlap, their individual weights are multiplied to form a new combined weight. For example, if an alcohol outlet polygon barrier overlapped with a school polygon barrier, and they were both scaled cost barriers, their weights would have been multiplied, and this *multiplied* value would have been applied to the portion of the street segment that passed through the overlapping polygon barriers. The Route Analysis tool would always therefore favour street segments that only pass through single barriers rather than overlapping barriers. Figure 8 below demonstrates another example where alcohol outlets and schools were given a scaled cost of two and three, respectively (these hypothetical weights were selected merely for demonstration purposes). When overlapped, their combined scaled cost would have been six (two multiplied by three).

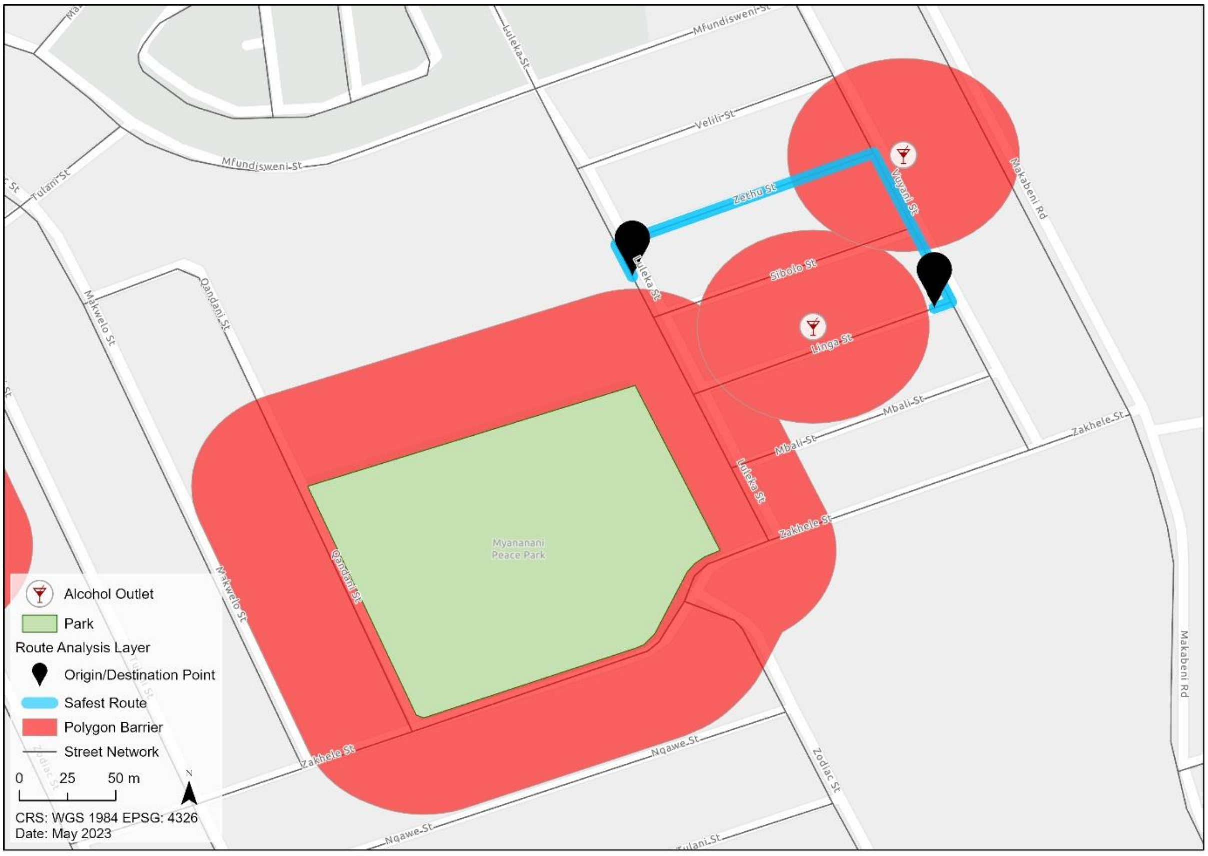

Figure 9: Map illustrating an example of overlapping polygon barriers

Figure 9 shows that the safest route (shown in blue) passes through only one polygon barrier (with a lower scaled cost) instead of passing through multiple overlapping polygon barriers. The suggested safest route only went through one polygon barrier (an alcohol outlet danger zone) and had a total geodesic length of roughly 231 metres, however, since it traversed a polygon barrier with a scaled cost of two, the resultant scaled length was approximately 323 metres. The reason why the total length was not doubled exactly (i.e., 462 metres) is because only the street segments that pass through the polygon barrier will experience the scaled cost. It is clear that passing through only one polygon barrier is favoured over passing multiple overlapping polygon barriers in this tool. Alfonso (2017) mapped safe walking routes to schools in California and assigned all polygon barriers in their study a standard scaled cost of *two* since it was assumed that all barriers impacted street safety equally. In a similar way, each polygon barrier in this method was given an equal weight of two. In this safest route analysis, if street segments intersected these polygon barriers, their length (metres) was multiplied by two and if a street segment intersected more than one barrier, their weights were multiplied respectively. Thus, the more barriers a street segment intersected, the greater their (the barriers) influence on street safety. Taking this into consideration, the safest route was found by minimising the distance travelled (setting the cost of travel to the street segment lengths in metres) *as well as* the number of barriers traversed when travelling from the origin to the destination point. Time and type of day was not considered in this method because facilities are temporally stagnant. It might be true that certain types of facilities may become more dangerous depending on the day of the week or time of the day, but this was not considered in this study. Future work should incorporate operating hours to each of the included facilities to analyse this effect.

Method 3: The safest walking route based on historical crime and weighted 'risky facilities'

The final method made use of both historical crime incidents as well as risky facilities to determine safe walking routes in Khayelitsha. This was done by measuring the intensity of crime surrounding each facility type and using this intensity value to assign a weight to each facility type. Thereafter, these weights were used as inputs for the scaled cost polygon barriers in the Route Analysis tool in ArcGIS Pro. So, unlike in Method 2 where all risky facilities were given the same weight (of two) based on the assumption that they all posed roughly the same 'risk' to pedestrians – in Method 3, each facility type was assigned a unique weight indicating their perceived relative risk to pedestrians based on their historical association with crime.

Consequently the aim was to assign each facility type (polygon barrier) a unique weight rather than an equal weight of two (as in Method 2).

To achieve this method, the following steps were taken: first, 50-metre buffers were generated around each risky facility and the number of crime incidents located within these buffers were summed per facility type. After summing the crime counts per facility type, these totals were divided by the respective number of facilities per facility type to get an average number of crime incidents per facility type. If facilities had a higher crime average, they were considered to be associated with a higher intensity of crime and were as a result, seen as having a potentially greater harmful influence on pedestrian's street safety. The average number of crime incidents around each type of facility are shown in Table 1 below.

Table 1: Crime intensity results per facility type (within 50m) in Khayelitsha

Facility Type	**Facility Count**	**Total Crime Count**	**Average Crime Count**
Alcohol Outlets	134	1524	11.37
Bus Stops	38	657	17.29
Parks	62	1045	16.85
Railway Stations	5	81	16.20
Schools	98	1187	12.11
Shopping Malls	4	107	26.75

Through rigorous testing, it was discovered that the Route Analysis tool in ArcGIS Pro is extremely sensitive to the values assigned to scaled cost polygon barriers. That is, the bigger the scaled cost, the more restrictive a polygon barrier becomes (recall the discussion regarding restriction polygon barriers earlier in the chapter). As a result, the crime averages per facility type (shown in Table 1) were simply too large to be used directly as scaled cost values for the facilities. If these large averages were used as the scaled costs, then each facility polygon barrier would essentially be treated as restriction polygon barriers and lose their 'unique' influence. For this reason, the averages were normalised to fall into a smaller range of values, i.e., ensuring the scaled cost values remain small enough to have an impact on the suggested route.

The scale for this normalisation was calculated to represent the influence that these different facilities had on crime in Khayelitsha. That is, instead of arbitrarily selecting a normalisation range of one to ten, testing was conducted to determine the most appropriate normalisation range. It was found that a range of between one to seven was most appropriate for the data. That is because when the polygon barriers were assigned values greater than seven, it was found that the Route Analysis tool avoided these polygon barriers completely and treated them as restriction polygon barriers. Therefore, it was decided to confine the crime intensity averages per facility type to a range between one to seven. In this scenario, a value closer to one indicates that a polygon barrier has a lower association with crime and is perceived as being less 'criminogenic', while values closer to seven represented facilities with a greater association with crime and thus perceived as being more 'criminogenic'. Figure 10 below demonstrates the testing that was conducted on each facility type to determine the abovementioned normalisation scale. In this example, schools were under investigation.

Figure 10: Map demonstrating how the weight of a school polygon barrier impacts the resultant route between two random points

In the example depicted in Figure 10 above, the blue route resembles the path taken when the school polygon barrier was assigned a scaled cost of one, ultimately having no added influence on the resultant route. Consequently, this blue route also represents the shortest route. When increasing the scaled cost to two, no difference was found and the blue route was still the optimal route. However, once the scaled cost was raised to a value of three, the resultant route changed slightly and is represented in yellow. It is clear that the route still went through the polygon barrier but avoided it slightly by selecting a street segment that was not covered by the polygon barrier as much as the adjacent street segment (keeping in mind that the Route Analysis tool applies the scaled cost only to the portion of the street segment that is covered by the polygon barrier). Similarly, when the scaled cost was given values from four to seven, no further difference was found in the resultant route and still suggested the yellow route. Finally, when the scaled cost was assigned to the value of ten, the polygon barrier was avoided completely, ultimately treating the polygon barrier as a restriction. Any value greater than ten had the same influence. Therefore, a value of ten was found to be the upper threshold (i.e., value at which the barrier becomes a restriction) for a school barrier. This process was repeated for each facility type to identify the average value at which barriers had no influence and the average value at which barriers were avoided completely.

When this process was repeated for each facility type individually, a value of *four* was found to be the upper threshold at which the suggested route avoided the *alcohol outlet* barriers completely, whereas a value of *13* was the upper threshold for *park* barriers. Both *bus stop* and *railway station* barriers were avoided completely using a value of *five* while a value of *six* avoided the *shopping mall* barriers completely. Therefore, it was subsequently found that *on average* across *all* facility types, the suggested routes avoided a polygon barrier *completely* when the weight was set to *seven*. This therefore demonstrates the process followed to determine the normalisation scale of one to seven.

It is important to note that determining appropriate weights for facility types was not the main focus of this study and therefore should be further investigated in future work. This research simply tested whether weighing the barriers differently had any influence on finding the safest routes between an origin and destination point. Subsequently, after the normalisation of the crime averages, each risky facility barrier was assigned a corresponding weight between one and seven. Ultimately, this route analysis was conducted similarly as *Method 2* (discussed previously), however, the polygon barriers (risky facility types) were assigned their respective weights rather than an equal scaled cost of two. This entire process (calculating the average crime counts per facility type and normalising it between one and seven to identify a unique weight) was applied to *all* crime, daytime crime (incidents occurring between 6:00 AM and 18:00 PM), night-time crime (incidents occurring between 18:00 PM and 6:00 AM), weekday crime (Monday to Friday) and weekend crime (Saturday and Sunday). This was done by selecting crimes that occurred during certain times of day and on certain types of days, respectively, similar to Method 1.

Chapter 5: Results

5.1 Method 1: The safest walking route based on historical crime

Figure 11 represents a street segment analysis of crime in the formal streets of Khayelitsha (in crime per metre).

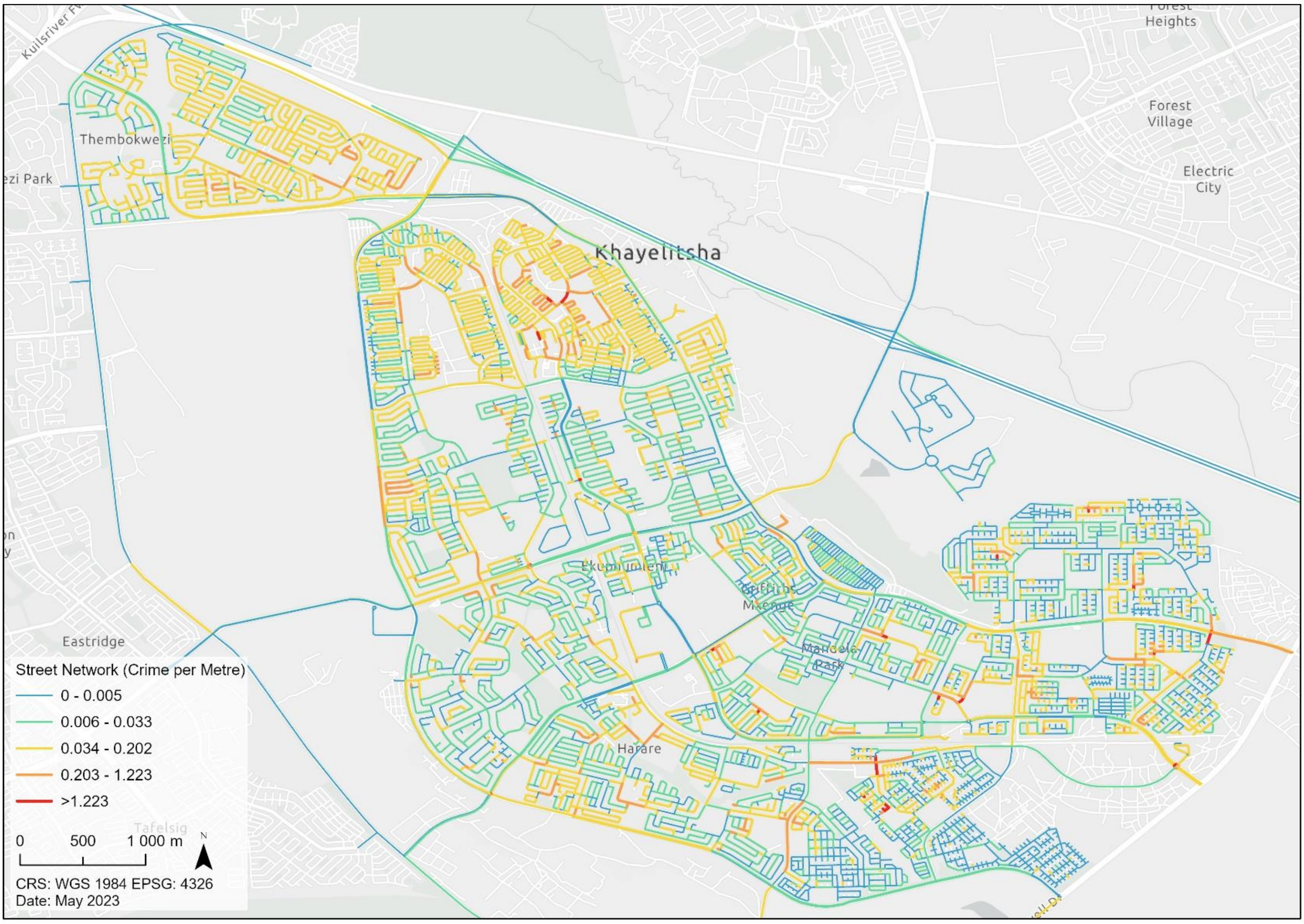

Figure 11: Map illustrating the crime per metre across Khayelitsha's street network

Street segments that experienced few crimes per metre are shown in shades of blue and green, whereas street segments that experienced moderate to high crime per metre are represented in shades of yellow, orange and red. Evidently, street segments with the highest crime counts per metre were mainly located in the centre and south-east parts of the township.

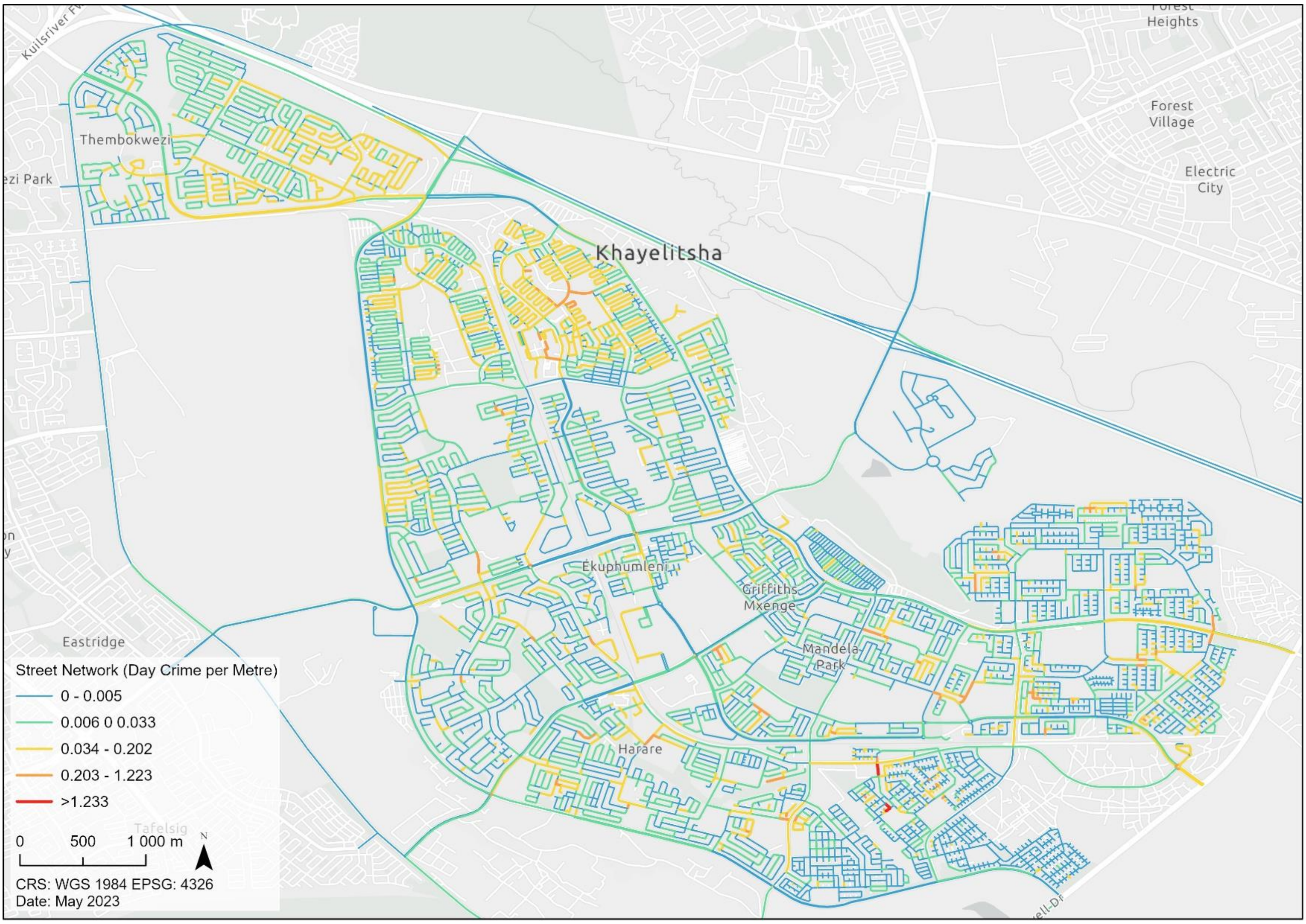

Figure 12: Map illustrating daytime crime per metre in Khayelitsha

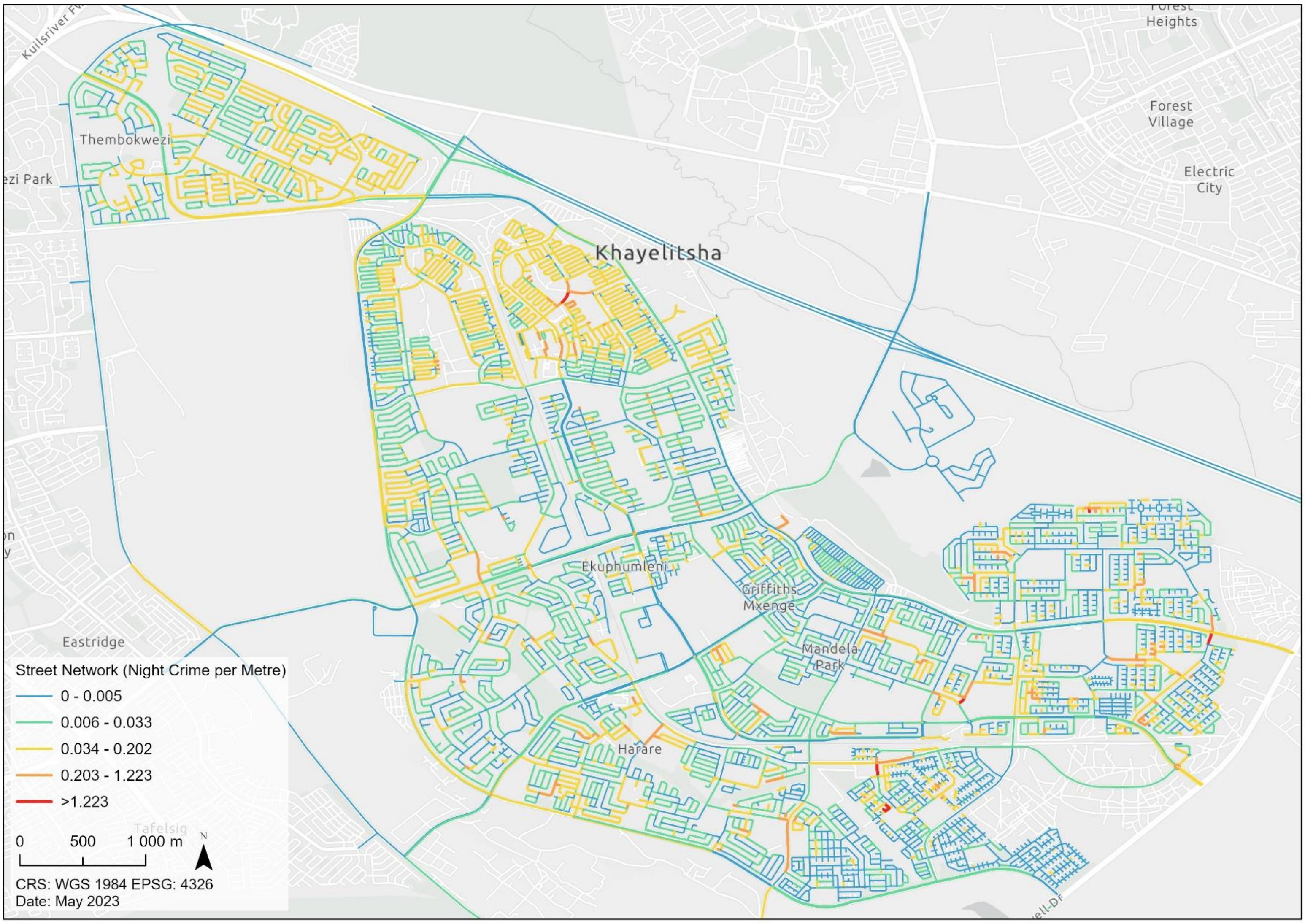

Figure 13: Map illustrating night-time crime per metre in Khayelitsha

Figures 12 and 13 illustrate the crime per metre for Khayelitsha for day and night-time, respectively. There were a few similarities between the results. First, there were a large number of street segments that experienced zero or low crime incident rates, displayed in blue and green across both time periods. For the daytime results, street segments with the highest crime incidents per metre were found in the southern part of Khayelitsha, relatively close to one another. This was similar to the night-time results, however, there were slightly more (roughly two to three) street segments for night-time than daytime, that were highlighted in red situated in the west and north regions of the township. Although the crime patterns are very similar for both time periods, these slight differences are what is most crucial to consider when determining safe walking routes in certain regions of Khayelitsha.

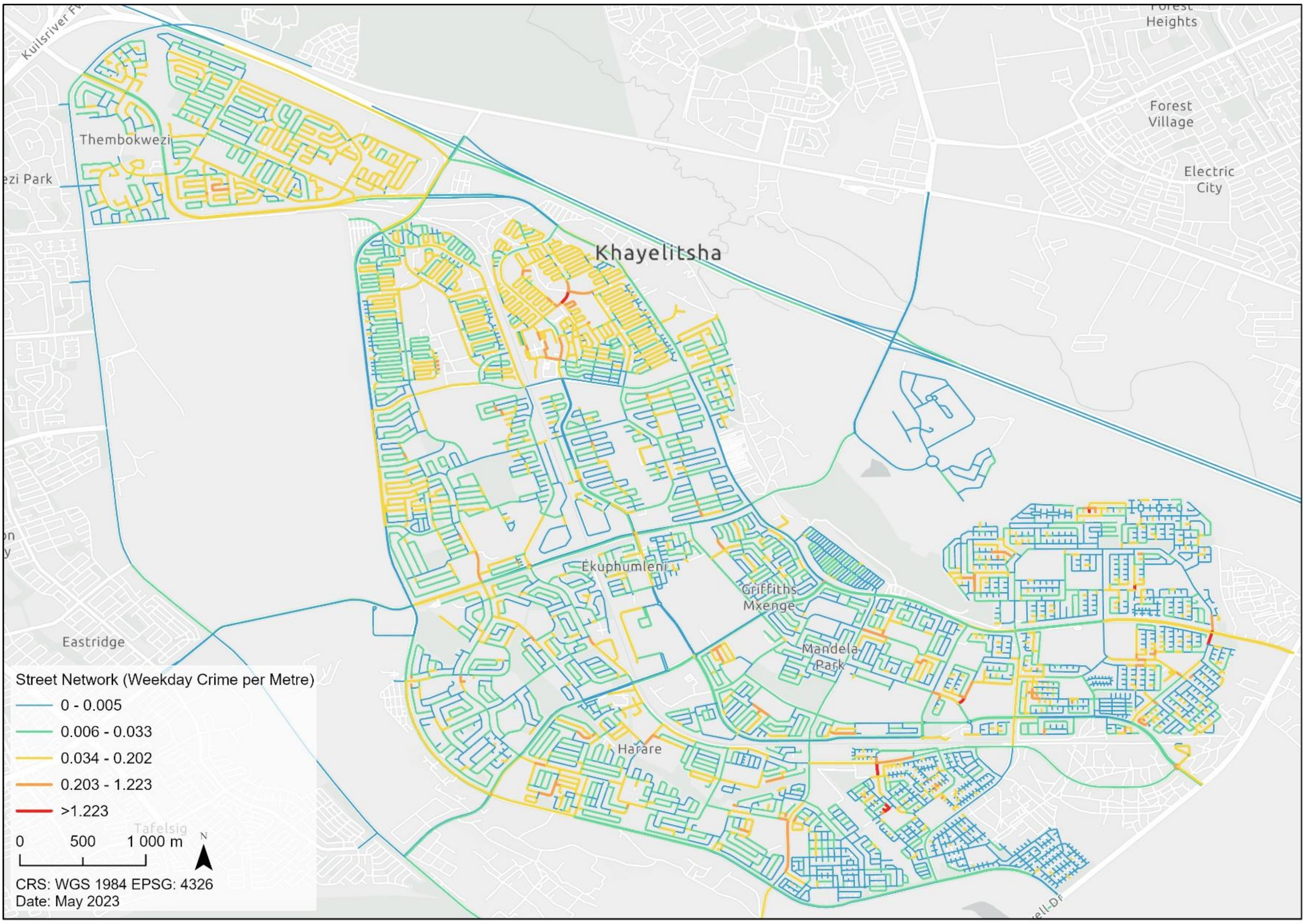

Figure 14: Map illustrating weekday crime per metre in Khayelitsha

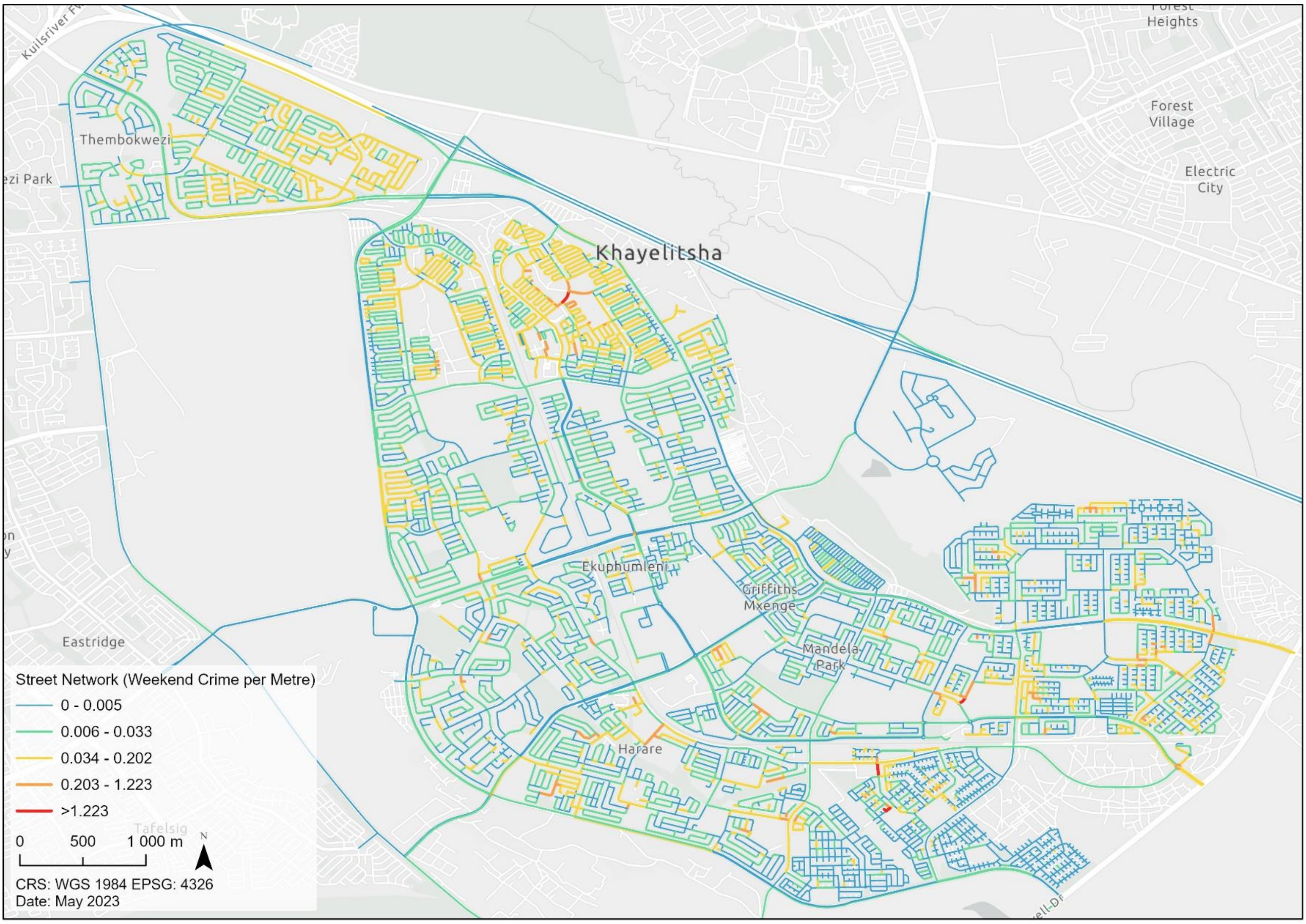

Figure 15: Map illustrating weekend crime per metre in Khayelitsha

Figures 14 and 15 above demonstrate the crime per metre during weekdays and weekends, respectively. Again, the results are rather similar with slight key differences. For both time periods, a number of street segments experienced zero to low crime incidents (shown in blue and green, respectively). There were fewer street segments, mostly located in the north-east region of the township, that were associated with moderate crime incidents per metre (shown in yellow) on a weekday and during the weekend. Again for both time periods, very few street segments (roughly five to ten) had high (in orange) and very high (in red) crime incidents per metre during the study period. There were slightly more street segments that experienced very high crime incidents per metre during the week compared to Saturdays and Sundays (weekend). There were the same low number (three or four) of street segments located in the north and south-west region of the township that were associated with an extreme amount of crime for both time periods.

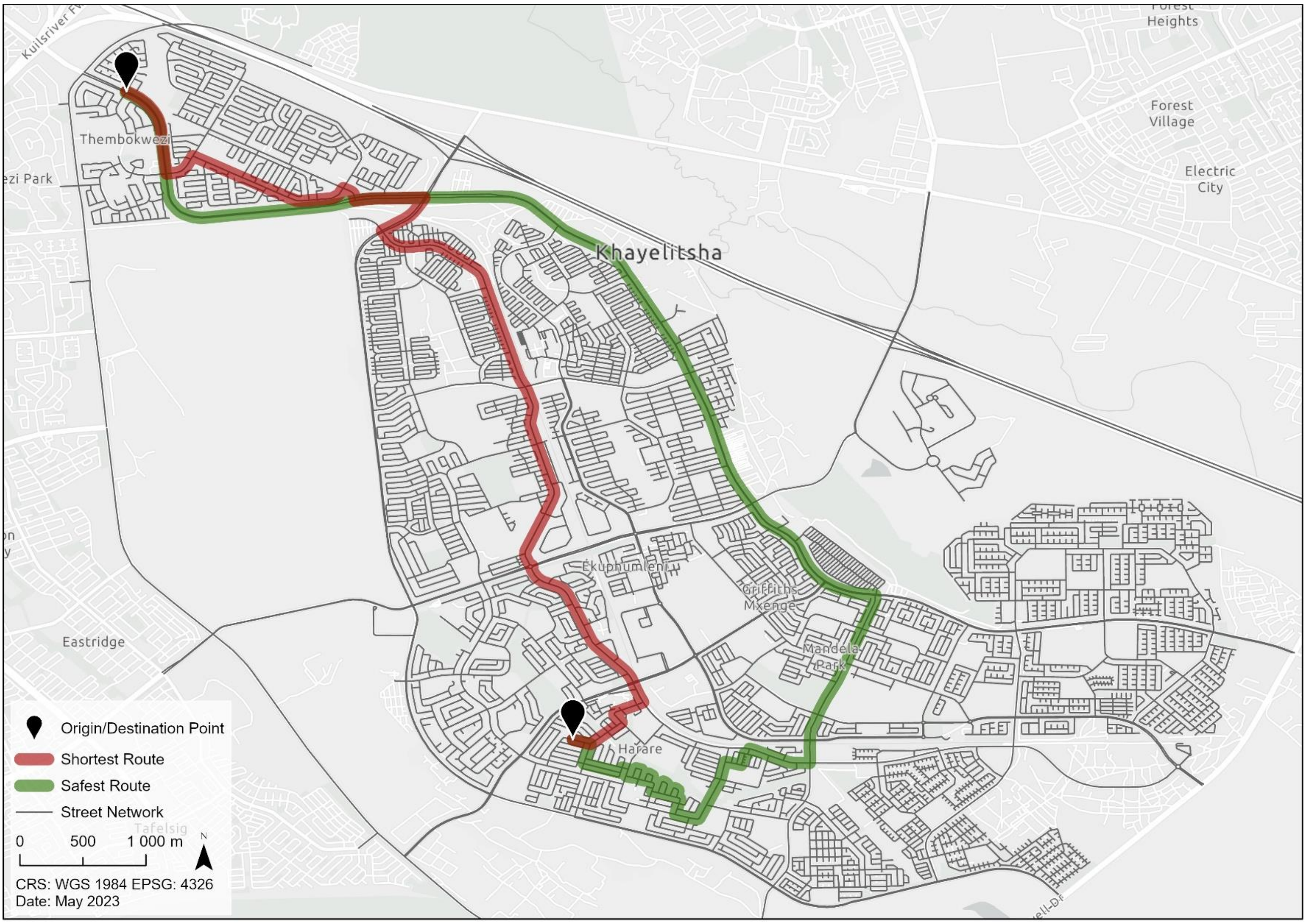

Figure 16: Map comparing the shortest and safest routes (based on crime) between an origin and destination point in Khayelitsha

Figure 16 shows the results of the calculation of the safest walking route in Khayelitsha using only historical crime data (Method 1). The shortest route between the two random points is shown in red while the safest route is shown in green. The shortest route between the two random points (red route) was roughly 8.4 kilometres long and traverses' streets that encountered a total of 735 historical crime incidents. There were approximately 7 crimes per metre along this route. On the other hand, the safest route (green route) had an approximate length of 12 kilometres and traverses' streets with a total historical crime count of 278 crime incidents, resulting in roughly 0.7 crimes per metre. As depicted in Figure 16, the shortest route differed greatly from the safest route where the safest route was roughly four kilometres longer. It is clear that the pedestrian would have had to walk a greater distance to reach their destination if they wished to follow a path that minimised the overall number of historical crime incidents per metre. However, despite the longer distance to walk, the safer route avoided just over 450 historical crime incidents in total, when compared to the shortest route. This clearly highlights how the crime risk was minimised in the safest route method whereas length was minimised in the shortest route, completely disregarding crime risk. Table 2 displays the total length (m), total crime count and total crime per metre for the shortest route and safest route, respectively.

Table 2: The shortest and safest route compared

Route	**Total Length (m)**	**Total Crime Count**	**Total Crime Count per Metre**
Shortest	8,370.35	735	7.60
Safest (All Crime)	11,985.50	278	0.72

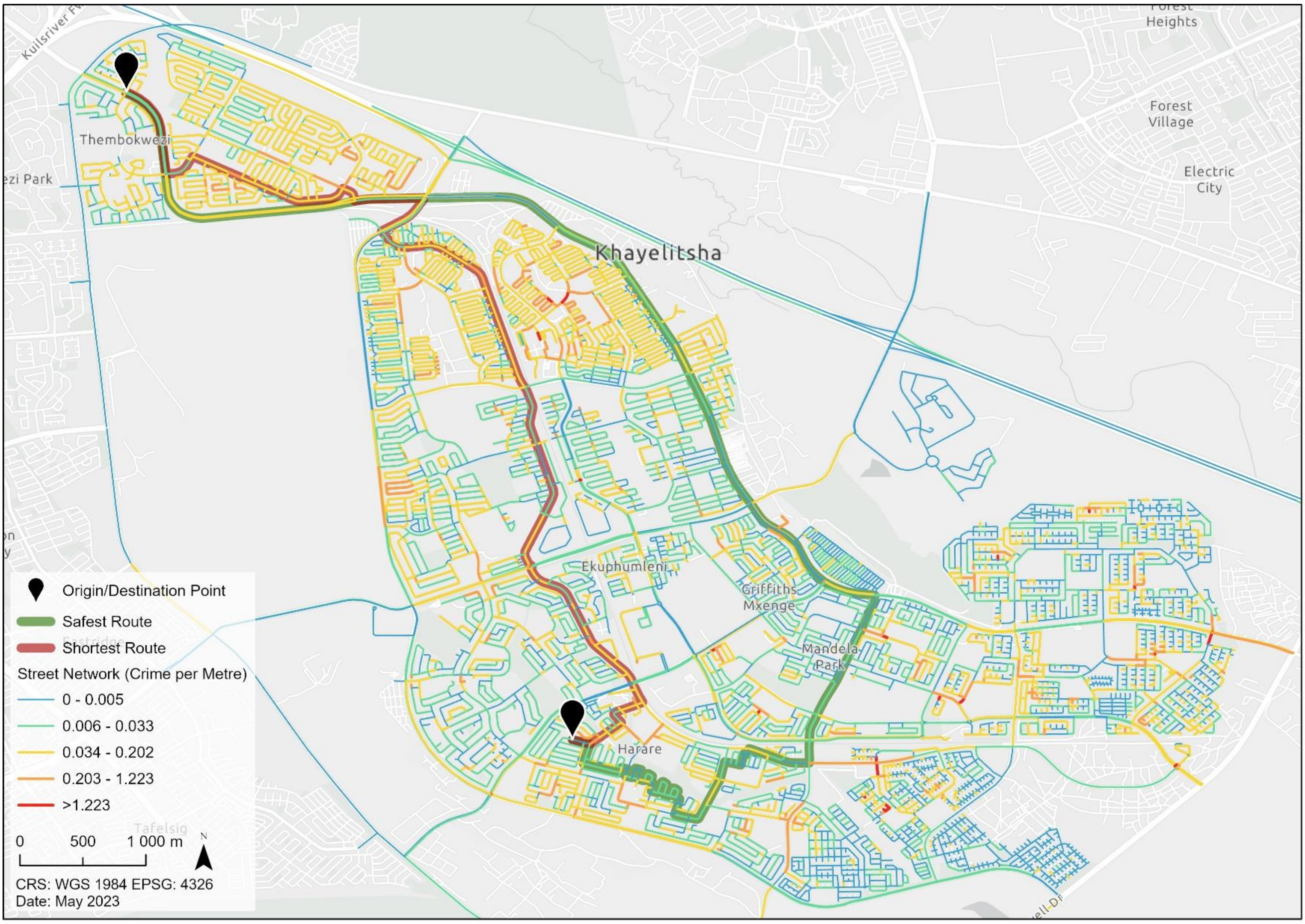

Figure 17: Map comparing the shortest and safest routes (based on crime) between an origin and destination point in Khayelitsha with crime per metre

Figure 17 shows the shortest and safest routes overlain on top of the street segment crime map. As is evident, the shortest route traversed more orange coloured street segments (indicating more crime per metre) than the safest route.

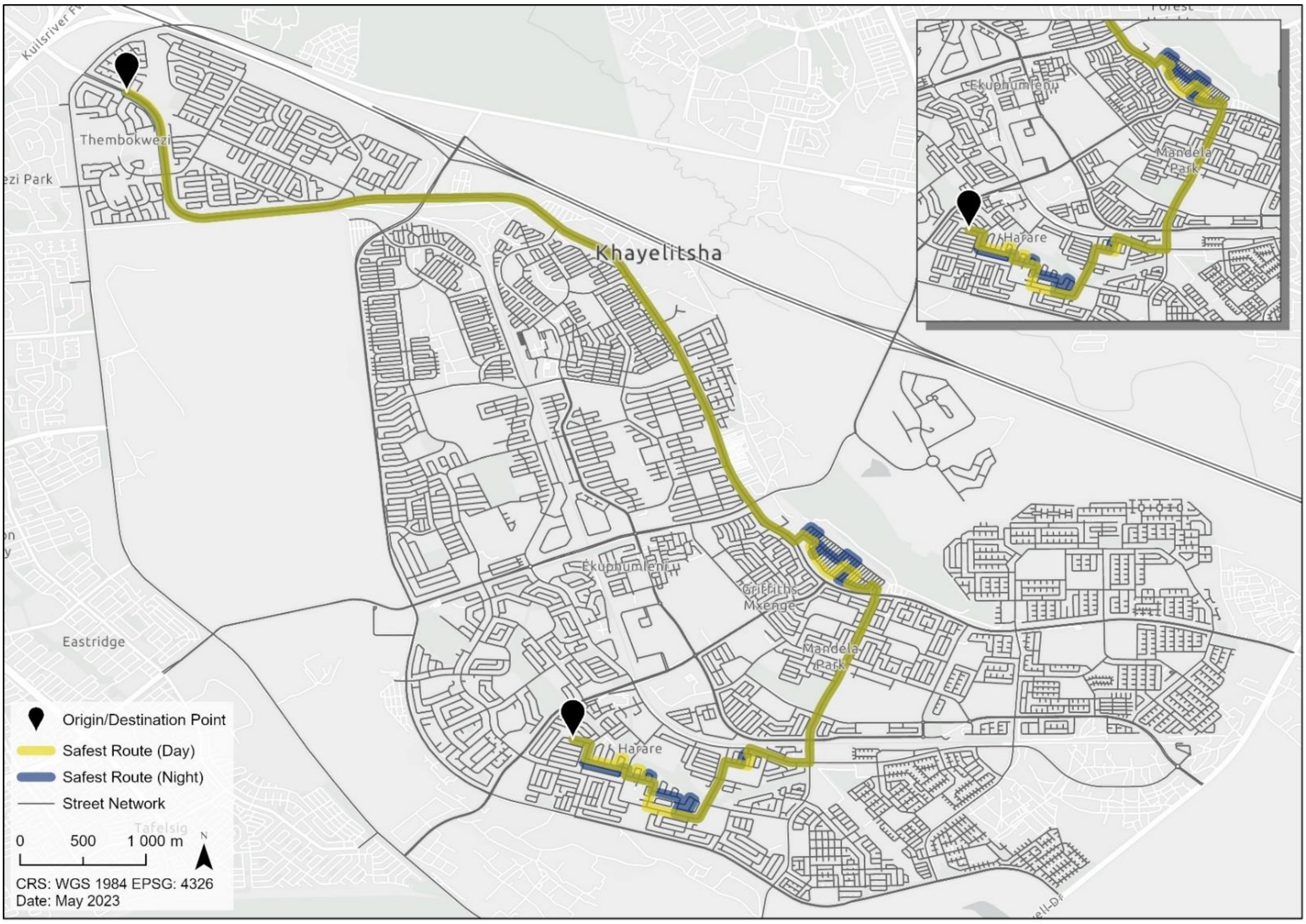

Figure 18: Map comparing the safest routes (based on crime) during the day and night between an origin and destination point in Khayelitsha

Figure 18 shows the safest walking route during the day (yellow) and the safest route during the night (blue) based on historical crime risk. The routes differed fractionally because some street segments experienced more daytime crime than night-time crime, although this difference is almost negligible. The inset map in the upper right corner highlights the small difference between these two routes. It was found that the safest route during the day was slightly shorter than the safest route during the night, with a total walking distance of 12.1 kilometres compared to 12.7 kilometres. Unsurprisingly, the safest route during the day had a slightly lower total historical daytime crime count than the safest route during the night (see Table 3). Similarly, the safest route during the night had a lower total historical night-time crime count of 134 historical crime incidents compared to the safest route during the day which had 159 historical crime incidents. Hence, the route with the least total historical daytime crime incidents was considered the safest route during the day, whereas a route with the least total historical night-time crime incidents was considered the safest route during the night.

Table 3: Results for the safest routes during the day and night

Route	Total Length (m)	Total Crime Count (Day)	Total Crime Count (Night)	Total Crime per Metre (Day)	Total Count per Metre (Night)
Safest (Day)	12,111.91	130	159	0.35	0.84
Safest (Night)	12,721.34	148	134	0.65	0.29

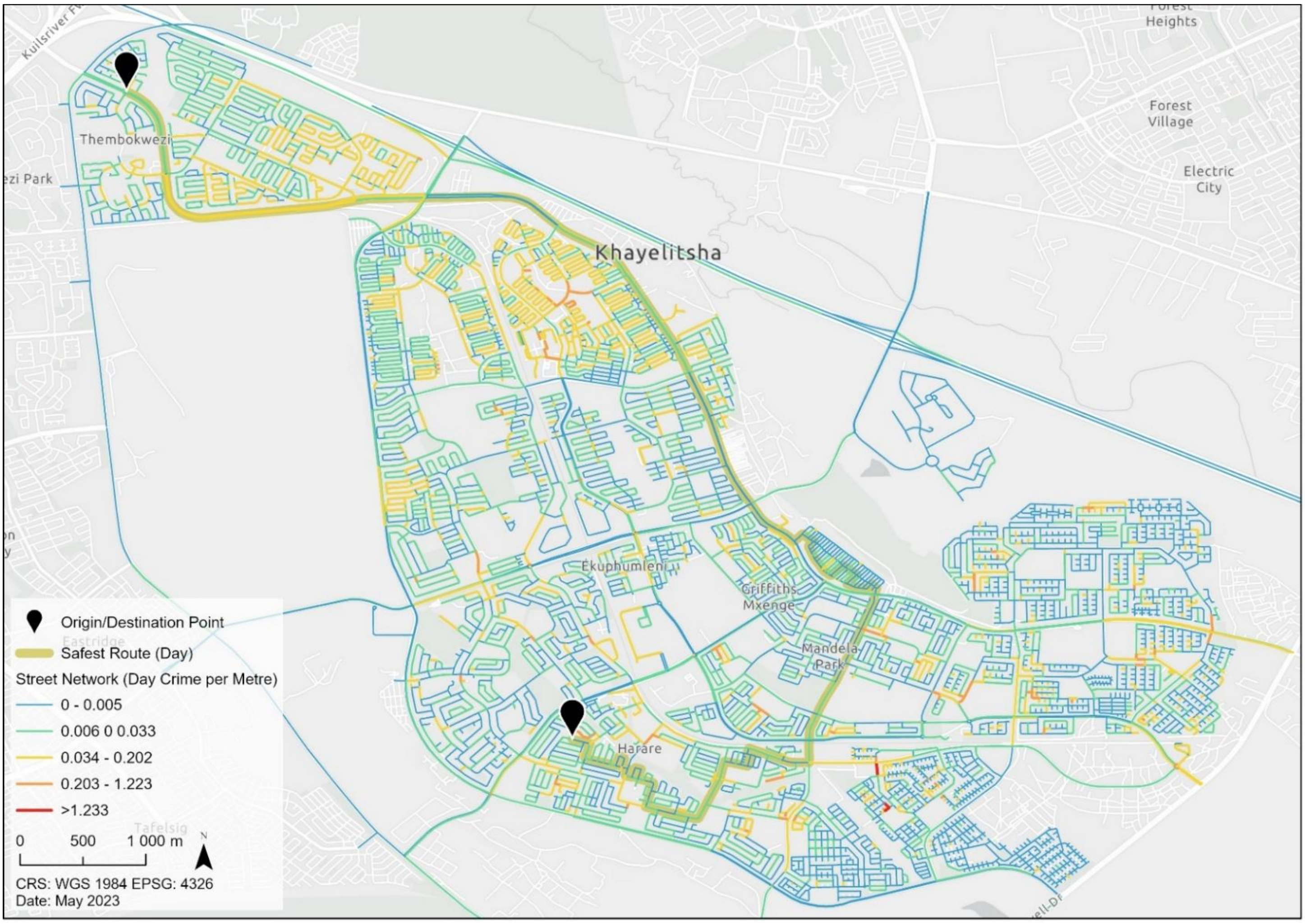

Figure 19: Map illustrating the safest route (based on crime) during the day in Khayelitsha with crime per metre

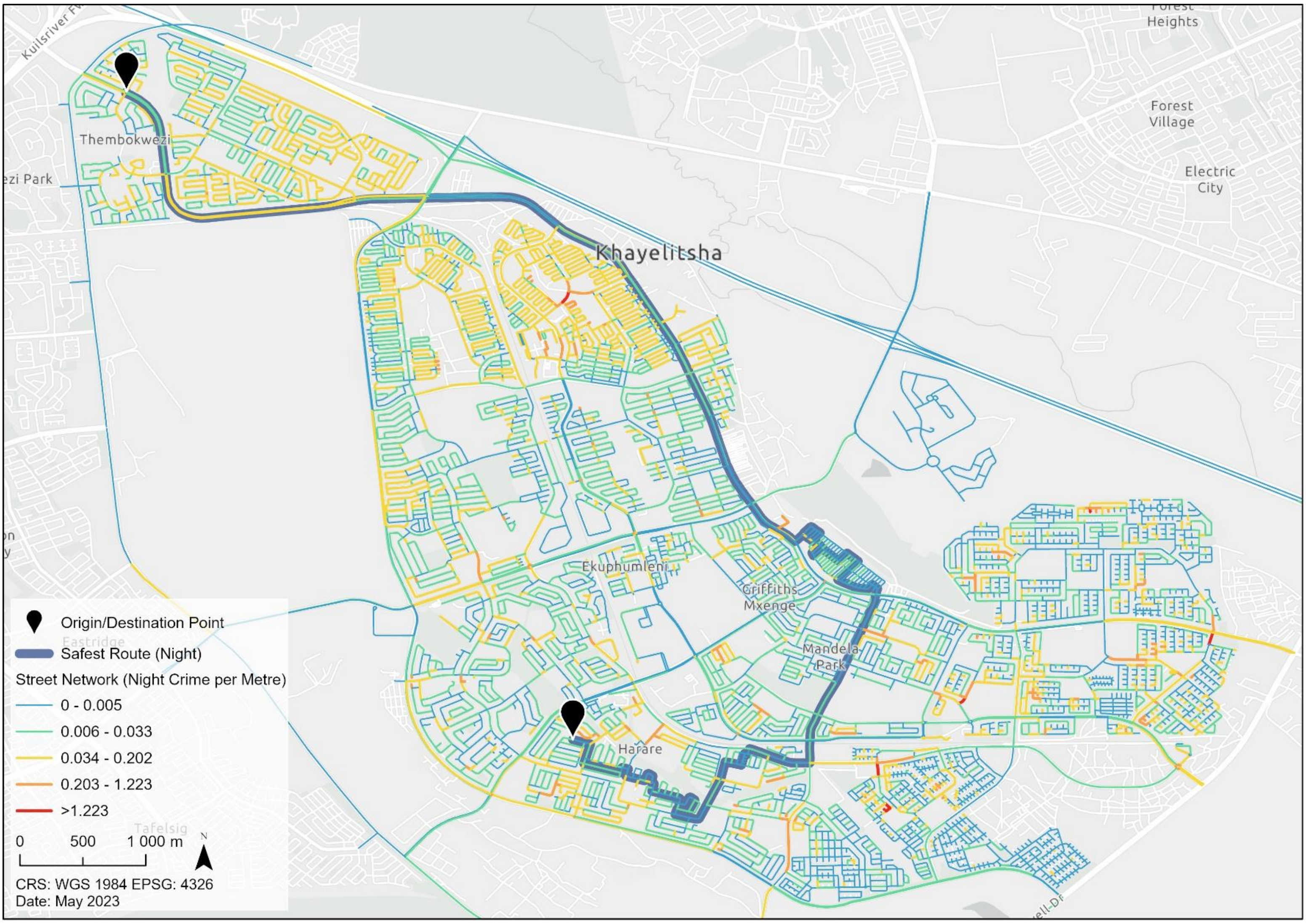

Figure 20: Map illustrating the safest route (based on crime) during the night in Khayelitsha with crime per metre

Figures 19 and 20 shows the safest daytime and night-time routes overlain on top of the street segment crime map. It is, again, confirmed that each route successfully minimised crime at the specified time of day, whereby in each case, yellow, amber and deep red street segments were mostly avoided.

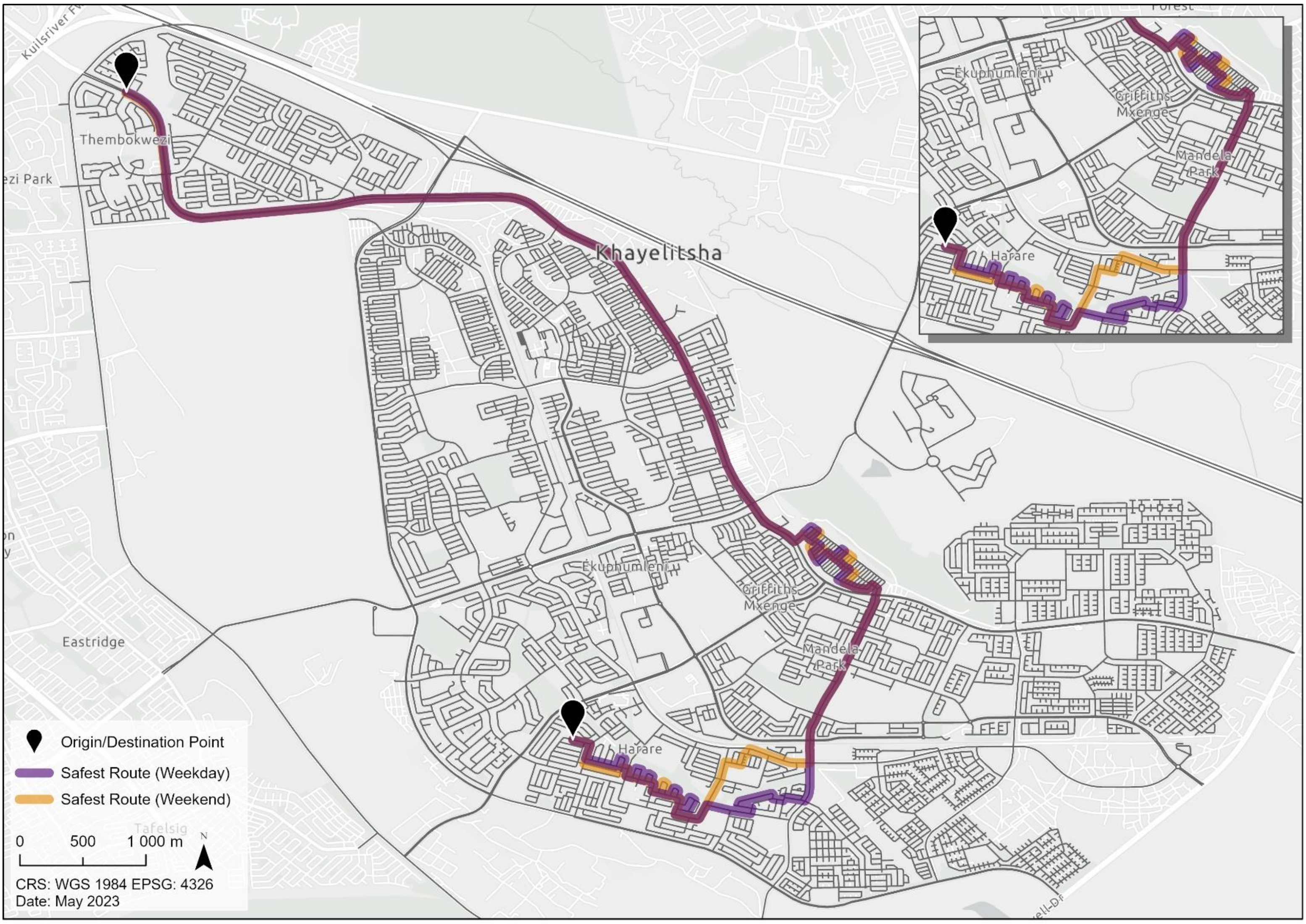

Figure 21: Map comparing the safest routes (based on crime) on a weekday and weekend between an origin and destination point in Khayelitsha

Figure 21 shows the safest walking route during the weekday (purple) and the safest route during the weekend (orange) based on historical crime risk. Once again, the safest walking route on a weekday was extremely similar to the safest route on the weekend – which indicates that crime risk was relatively uniform across the township regardless of whether it was a weekday or a weekend. Certain street segments experienced marginally less crime on weekdays than on weekends which somewhat influences the safest routes to walk when specifying type of day in Khayelitsha. The inset map in the upper right corner highlights the difference between these two routes. It was found that the safest route on a weekday was roughly one kilometre longer than the safest route during the weekend, with a total walking distance of approximately 13.2 kilometres compared with 12.3 kilometres. The safest route on a weekday had a total of 183 historical weekday crime incidents and the safest route during the weekend encountered merely 81 historical weekend crime incidents. Table 4 compares the results for the safest route on a weekday versus the safest route on the weekend.

Table 4: Results for the saftest routes (based on crime) on a weekday and weekend

Route	**Total Length (m)**	**Total Crime Count (Weekday)**	**Total Crime Count (Weekend)**	**Total Crime per Metre (Weekday)**	**Total Crime per Metre (Weekend)**
Safest (Weekday)	13,159.07	183	126	0.45	0.87
Safest (Weekend)	12,311.53	200	81	0.75	0.17

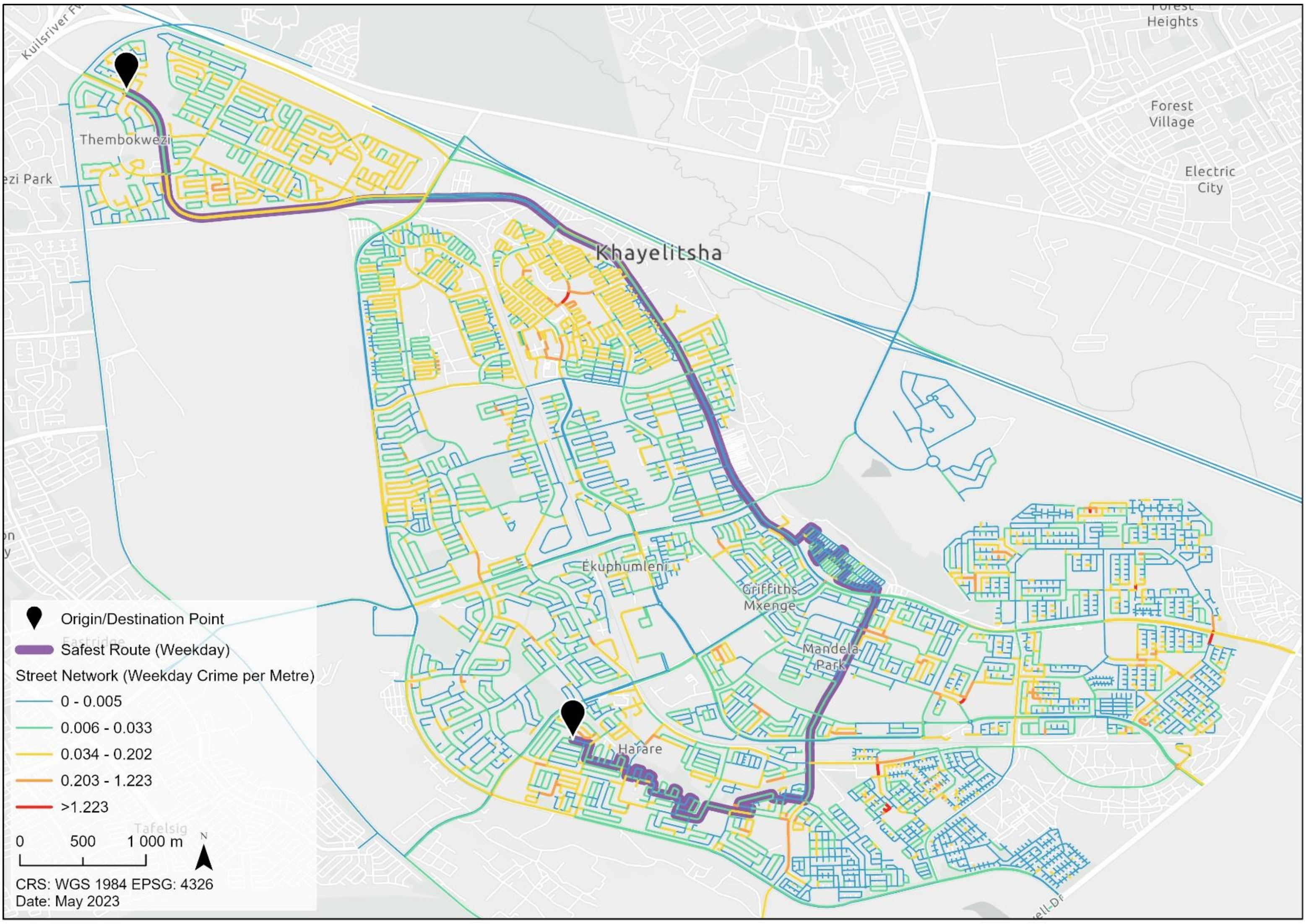

Figure 22: Map illustrating the safest route (based on crime) on a weekday in Khayelitsha with crime per metre

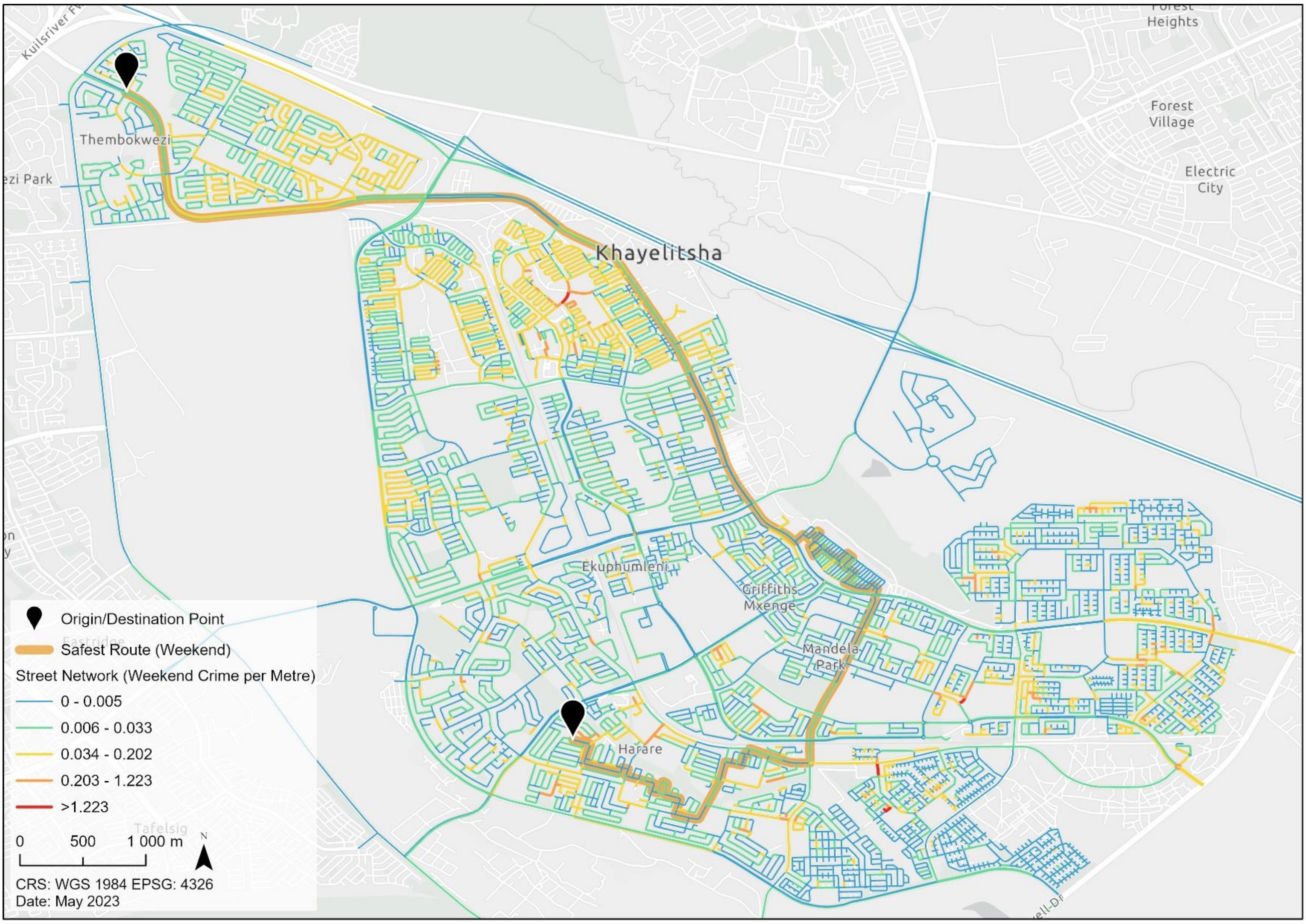

Figure 23: Map illustrating the safest route (based on crime) on the weekend in Khayelitsha with crime per metre

Figures 22 and 23 indicates the safest routes on weekdays and weekends, over with the underlying crime data. Again, each route successfully minimised crime risk at the specified time of day.

5.2 Method 2: The safest walking route based on 'risky facilities'

Figure 24 illustrates how the 50-metre buffer zones were created around each risky facility to represent their corresponding 'danger zone'. These buffer zones were used as route polygon barriers for the analysis in the Route Analysis tool in ArcGIS Pro.

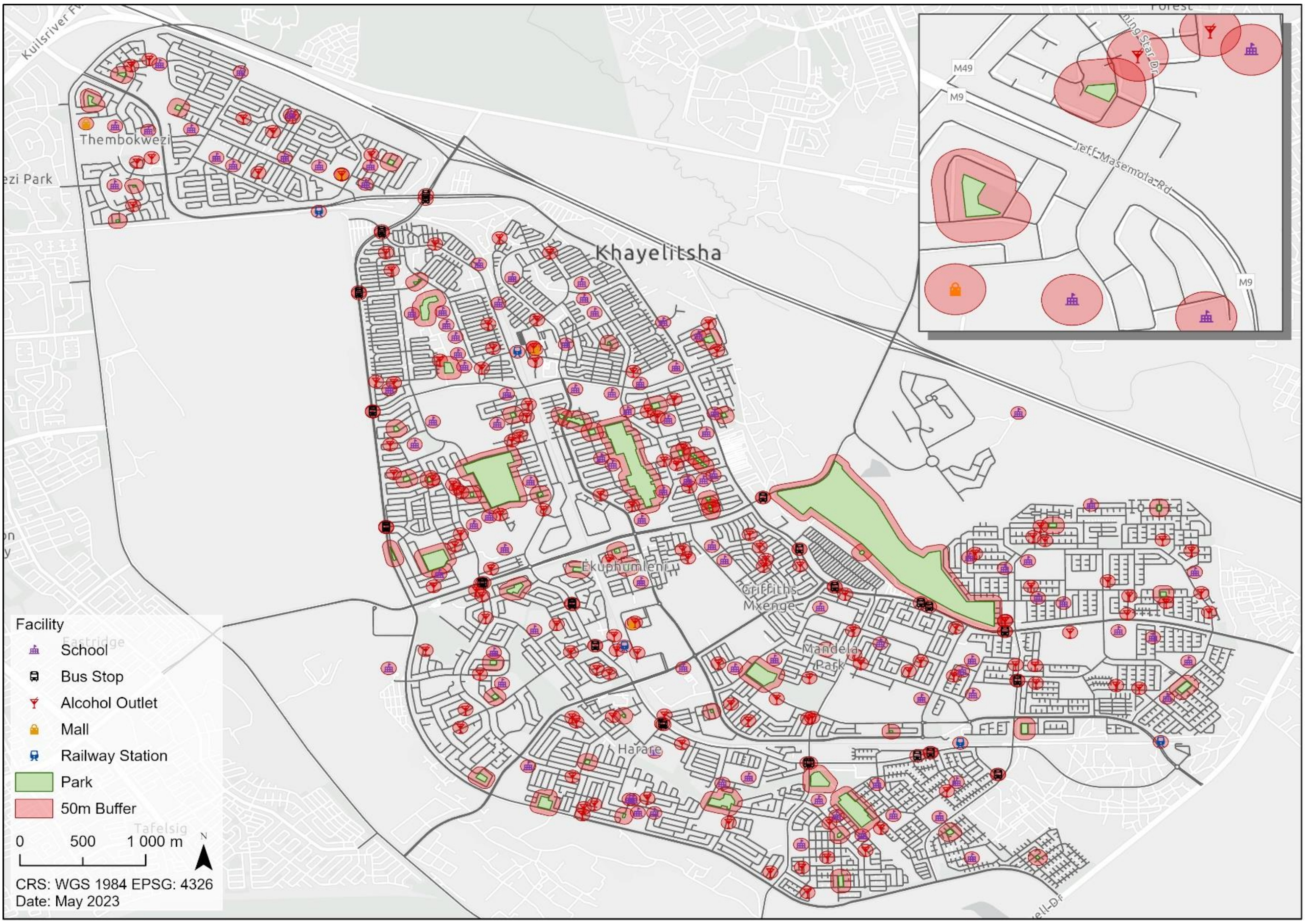

Figure 24: Map illustrating the 50-metre buffer zones around each risky facility in Khayelitsha

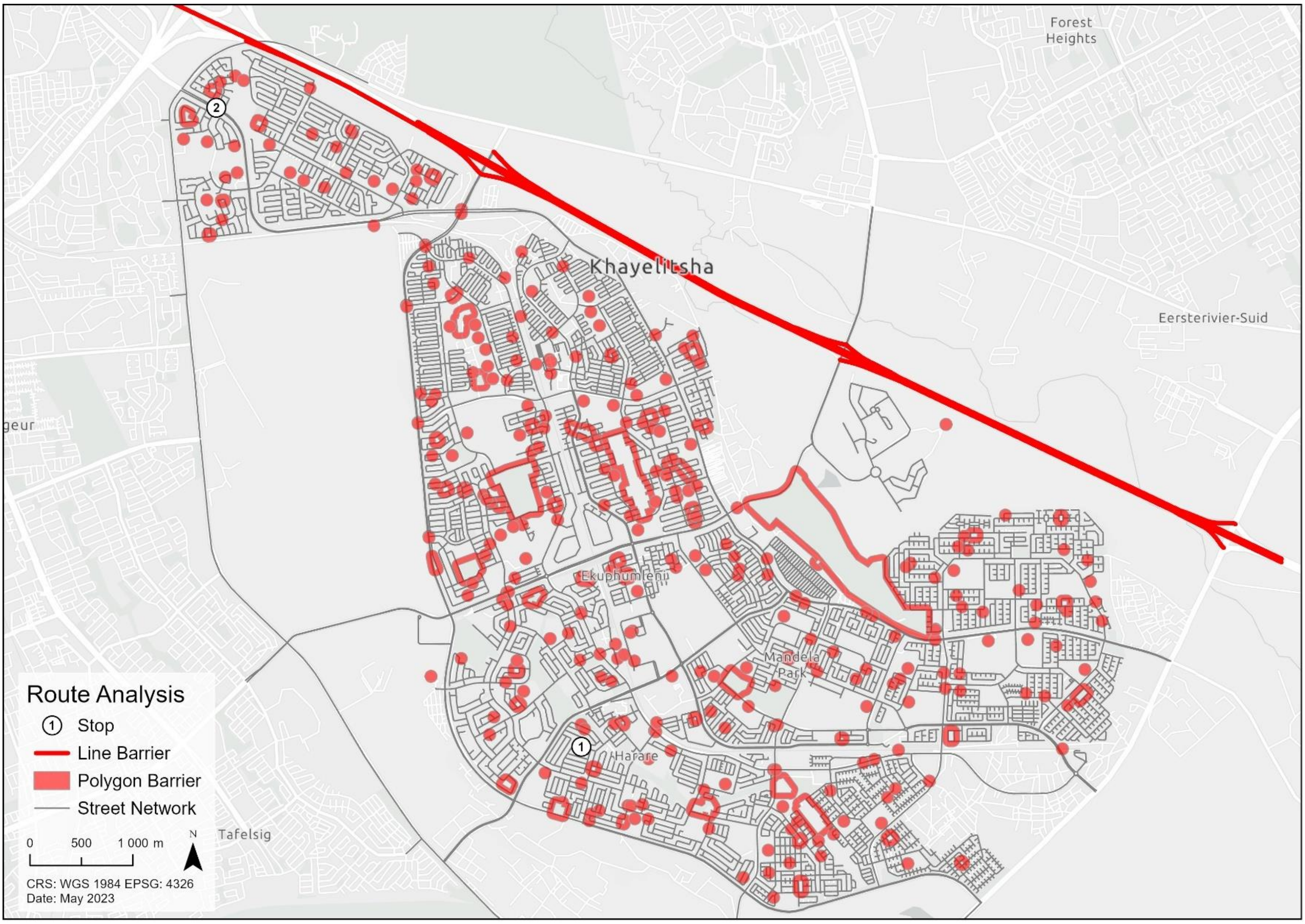

Figure 25: Map illustrating the route analysis layer in Khayelitsha

Figure 25 shows the street network dataset, route stops (origin/destination points), line barriers and polygon barriers combined. It is important to highlight that the parks themselves were not included, only the 50-meter danger zones surrounding them (hence their zones appear hollow).

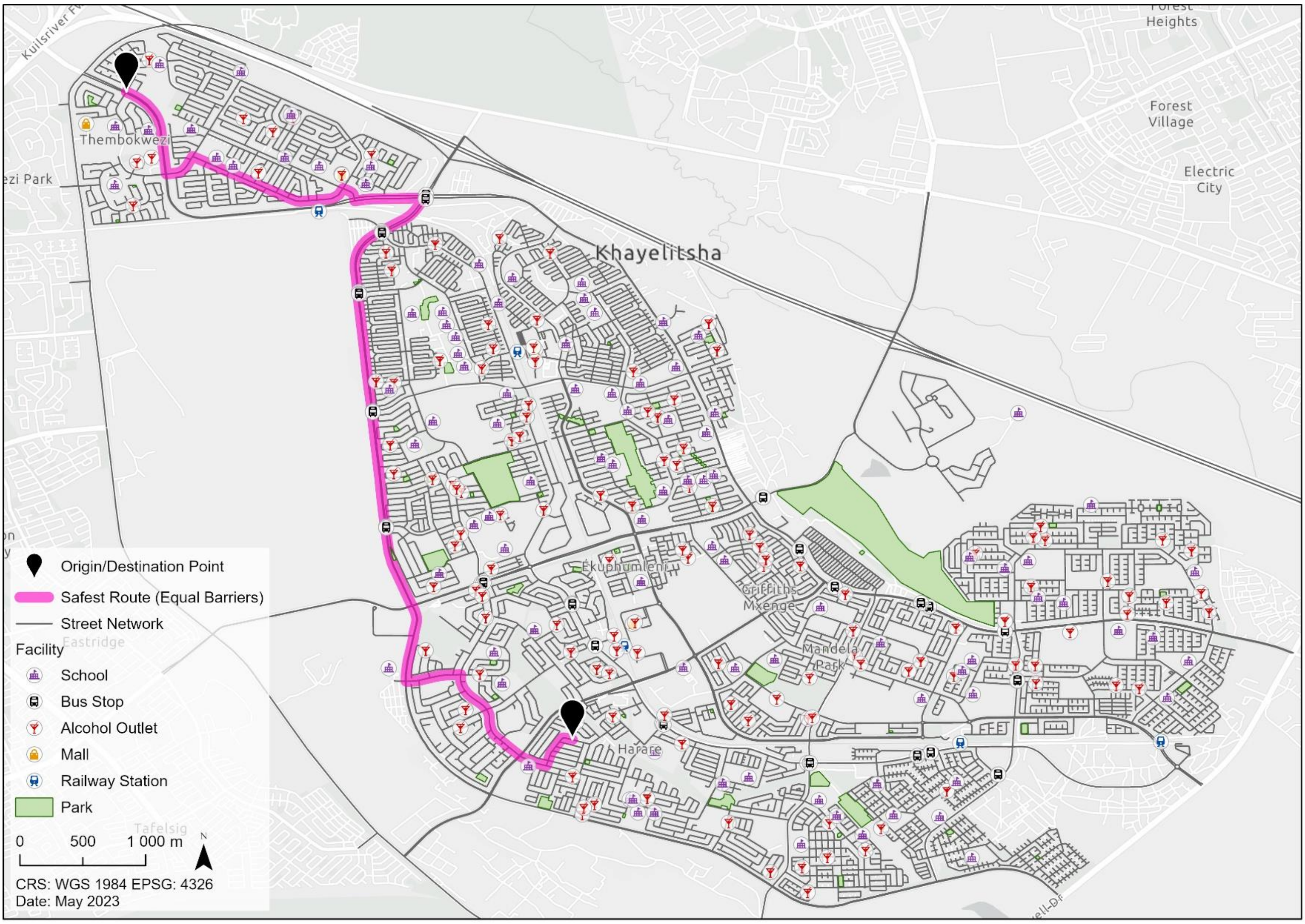

Figure 26: Map illustrating the safest route (based on equal polygon barriers) between two points in Khayelitsha

Figure 26 shows the safest route (in pink) between the same origin and destination point as Method 1 but in this analysis, only the ‘risky facilities’ were taken into account. Similar to Alfonso (2017), each so-called risky facility was assigned a standard scaled cost value of *two* so that any street segments that intersected with the barriers were regarded as ‘twice as unsafe’ as other street segments that did not intersect with any barrier.

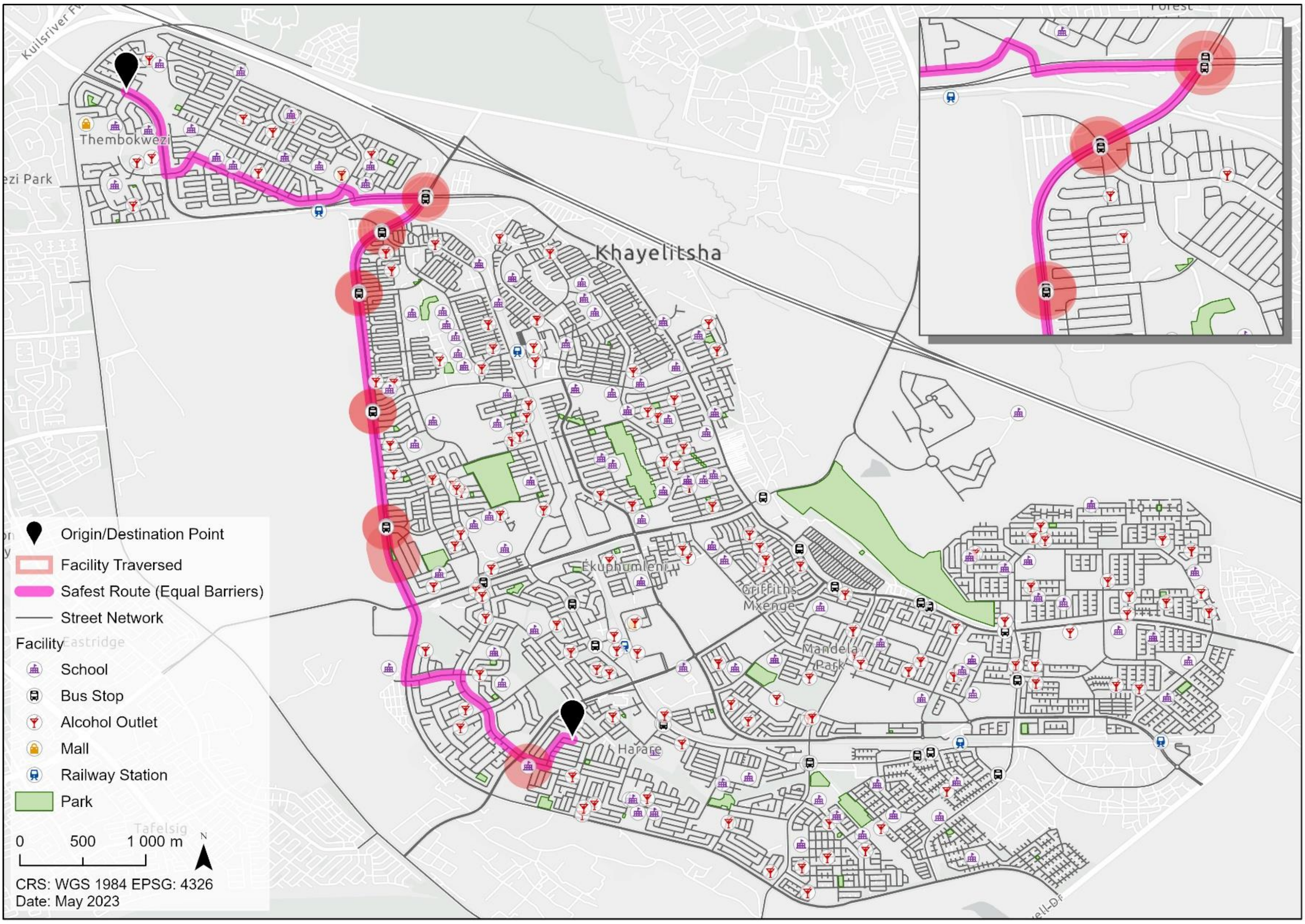

Figure 27: Map illustrating the barriers traversed along the safest route (based on equal polygon barriers) in Khayelitsha

Although this route was the safest, it still traversed 12 barriers (i.e. encountered risky facilities), of which 10 were bus stops, one was a park, and one was a school (see Figure 27). Therefore, at a scaled cost of two, these risky facilities (barriers) are only avoided until a certain point. Perhaps at a larger scaled cost value, the barriers would be avoided completely, and a much longer route may have been suggested. This resultant safest route was roughly 8.4 kilometres long and encountered a total of 601 historical crime incidents along the way (n = 4.62 crimes per metre).

5.3 Method 3: Finding the safest walking route based on crime and risky facilities

Table 5 below shows the average number of crimes within 50 metres of a facility per type in Khayelitsha.

Table 5: Average number of crimes per facility type (within 50 metres) in Khayelitsha

Facility Type	Facility Count	Total Crime Count	Average Crime Count
Alcohol Outlets	134	1524	11.37
Bus Stops	38	657	17.29
Parks	62	1045	16.85
Railway Stations	5	81	16.20
Schools	98	1187	12.11
Shopping Malls	4	107	26.75

Shopping malls had the greatest intensity of crime with an average of roughly 27 crime incidents per facility. Alcohol outlets and schools had the lowest crime intensity values of roughly 11 and 12 crime incidents on average, respectively. Railway stations were associated with slightly more crime, with approximately 16 crime incidents per station on average across Khayelitsha. Bus stops and parks were both found to have about 17 crime incidents on average within a 50 metre radius. These results indicate that *all* facilities were in fact spatially associated with crime in Khayelitsha (between 2012 and 2016). Of these six facilities, shopping malls had the greatest spatial association with crime. It is therefore expected that street segments adjacent to shopping malls are to be largely avoided.

In order to assign a weight to each facility, the first step was to convert these averages into values ranging between zero and one. This was done by taking the individual average value for each facility and dividing it by the total (see Table 6 below). For parks for example, the average crime count value of 16.85 was divided by the total value of 100.58 to get 0.17. In order to convert the range to be between one and seven, these values (currently between zero and one) were multiplied by seven and then increased by one. This ensured the weights were normalised to a new range starting at one and ending at seven. A value of one was added to these values because scaled costs should not begin at zero when using polygon barriers in the Route Analysis tool in ArcGIS Pro. Table 6 illustrates how each of these six facility types were assigned an appropriate weight between one and seven. It highlights the average number of crimes per facility type as well as the weights calculated per facility type.

Table 6: Weight per facility type

Facility Type	**Average Crime Count**	**Conversion (0 – 1)**	**Multiply by 7**	**Add 1**
Alcohol Outlets	11.37	0.11	0.79	1.79
Bus Stops	17.29	0.17	1.20	2.20
Parks	16.85	0.17	1.17	2.17
Railway Stations	16.20	0.16	1.13	2.13
Schools	12.11	0.12	0.84	1.84
Shopping Malls	26.75	0.27	1.86	2.86
Total	100.58	1.00	7.00	8.00

These weights were then used as inputs for the ArcGIS Pro Route Analysis tool when specifying the scaled cost value for each barrier in Khayelitsha. In other words, when each barrier (danger zones for each facility type) was inputted into the tool, they were each assigned their corresponding weight values (see Table 6) to provide a better representation of their crime risk and potential influence on pedestrian safety. In this case, instead of assigning each barrier a value of two for all polygon barriers (like in Method 2), they were rather assigned unique corresponding values.

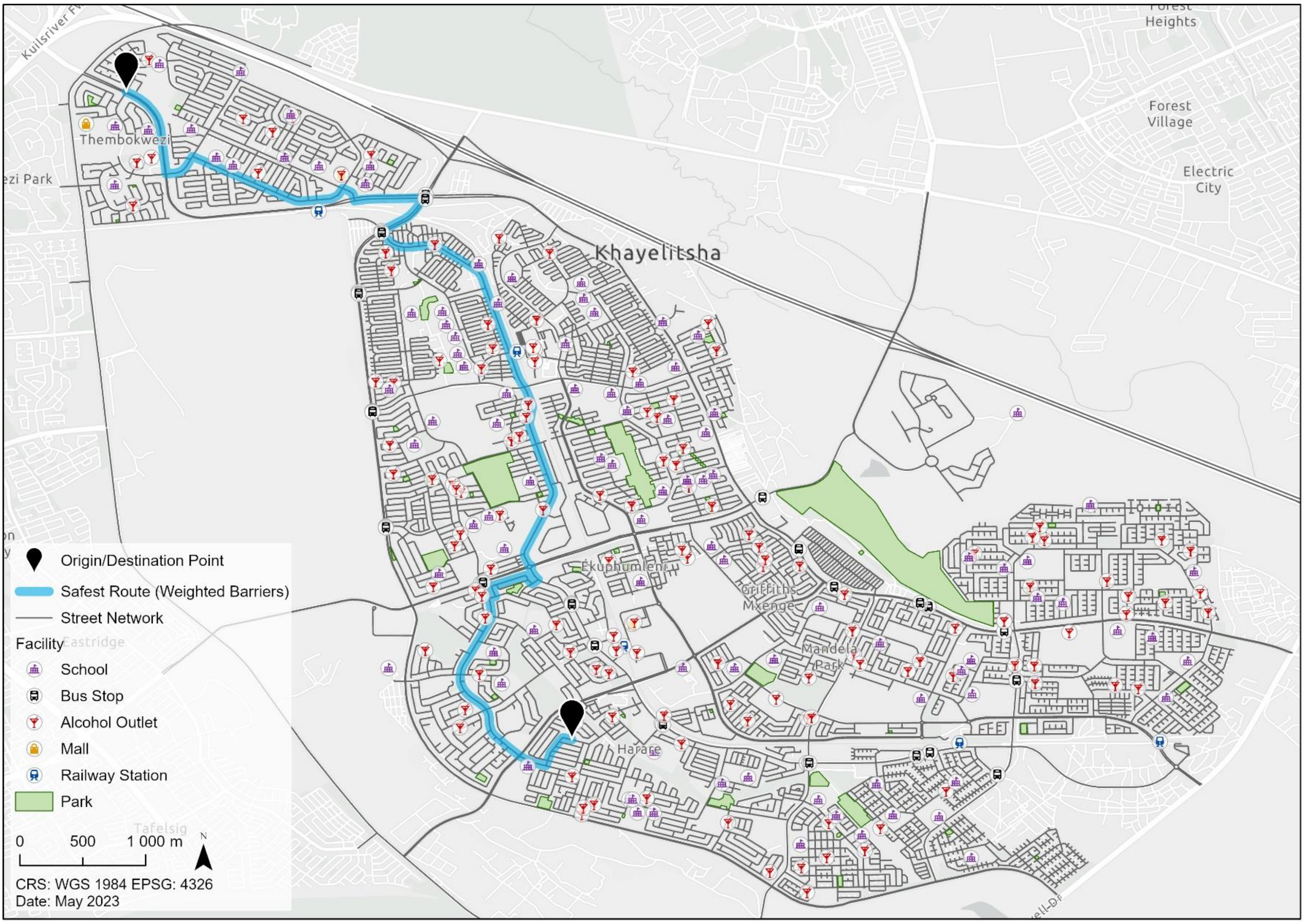

Figure 28: Map illustrating the safest route (based on weighted polygon barriers) between two points in Khayelitsha

Figure 28 shows the safest route to travel based on weighted risky facilities (polygon barriers in the Route Analysis tool). By avoiding these weighted polygon barriers, the safest route had a total length of 8.9 kilometres, which was slightly longer than the route avoiding the equal weighted barriers. This route encountered a total of 699 historical crime incidents along the way (n = 7.65 crimes per metre).

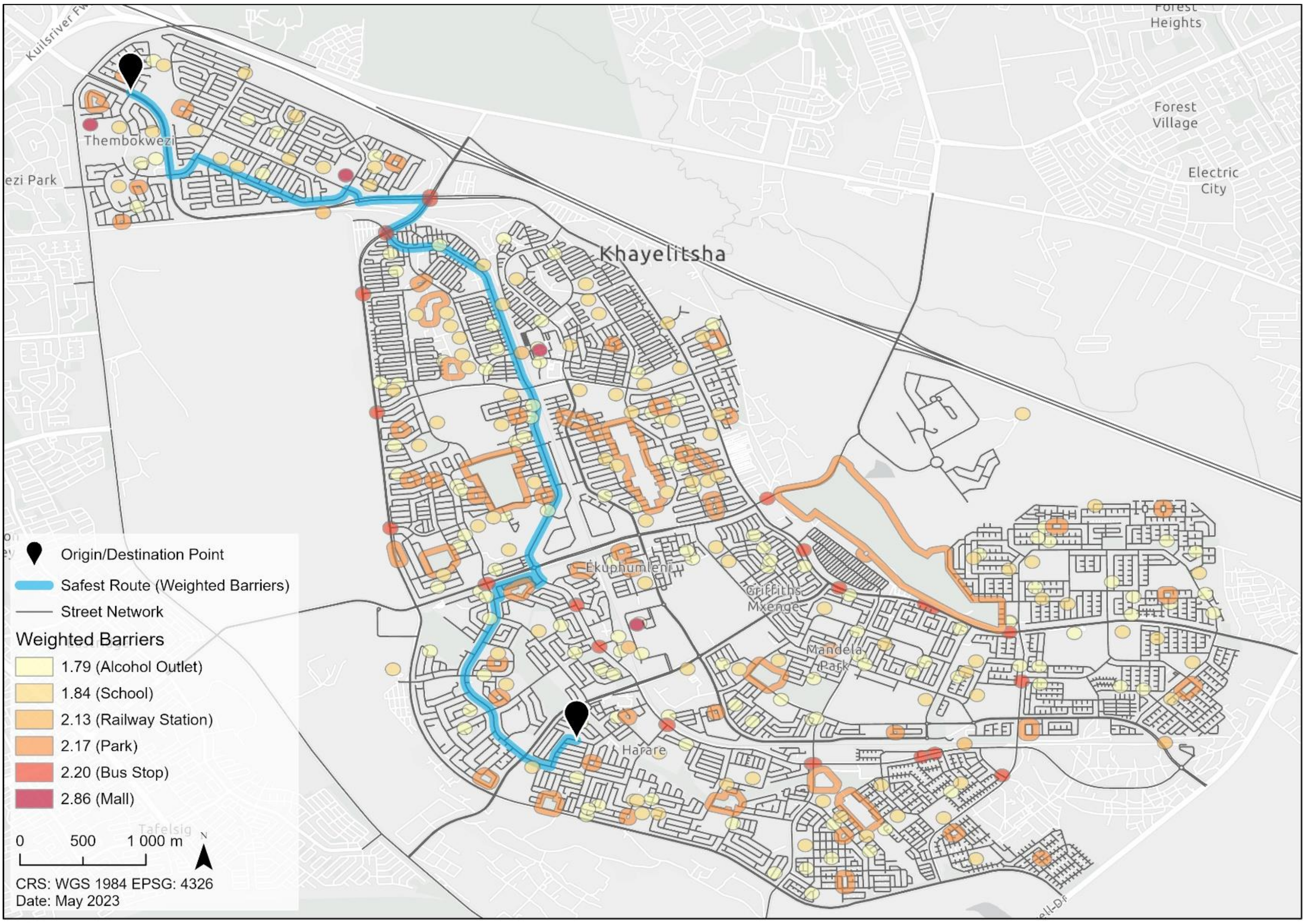

Figure 29: Map illustrating the weighted barriers (for all crime) used in Method 3

Figure 29 (above) illustrates the weighted risky facilities used to determine the safest walking route (considering all crime) in Method 3. It is clear that the resultant safest route traversed more polygon barriers that had lower weights (depicted in lighter yellow and orange) than other alternative routes. Although alternative routes may have been shorter with fewer polygon barriers, those other barriers possessed higher weights (shown in dark orange and red), therefore making it more unsafe than the suggested route. This was also repeated for day, night, weekday and weekend crime.

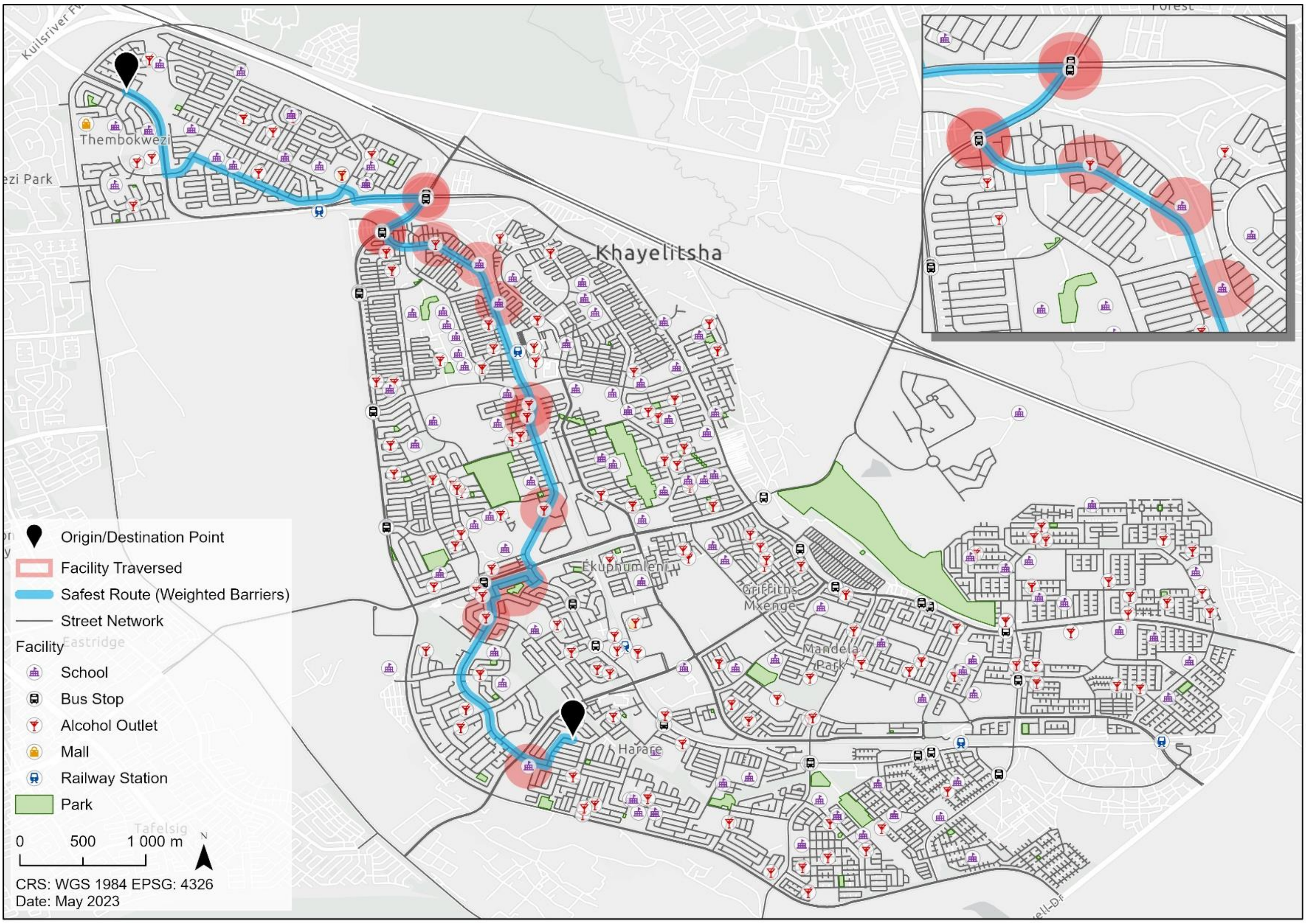

Figure 30: Map illustrating the barriers traversed along the safest route (based on weighted polygon barriers) in Khayelitsha

Figure 30 shows which facilities were traversed when following the safest walking route in Khayelitsha based on weighted risky facilities. Even though this route traversed a total of 13 barriers, it still represented the safest route when minimising the number of uniquely weighted barriers in Khayelitsha. This route encountered five alcohol outlets (lowest weight of 1.79), four bus stops (weight of 2.20), one park (weight of 2.17) and three schools (second lowest weight of 1.84). This route encountered the least amount of weight (added cost) while minimising the total distance travelled.

Table 7 displays the crime intensity results for daytime crime versus night-time crime.

Table 7: Crime intensity results per facility type for daytime crime versus night-time crime

Facility Type	Facility Count	Crime Count (Day)	Crime Count (Night)	Average Crime Count (Day)	Average Crime Count (Night)
Alcohol Outlets	134	633	880	4.72	6.57
Bus Stops	38	305	344	8.03	9.05
Parks	62	408	634	6.58	10.23
Railway Stations	5	42	39	8.40	7.80
Schools	98	546	616	5.57	6.29
Shopping Malls	4	65	41	16.25	10.25

Shopping malls had the highest crime intensity during the day with roughly 16 crime incidents per facility on average. On the other hand, alcohol outlets had the least crime incidents per facility on average during the day with a total of roughly five incidents. Both shopping malls and parks experienced the highest association with crime during the night with roughly 10 crime incidents per facility on average. However, schools had the smallest association of roughly six incidents per facility on average during the night.

Table 8: Crime intensity results per facility type for weekday crime and weekend crime

Facility Type	Facility Count	Crime Count (Weekday)	Crime Count (Weekend)	Average Crime Count (Weekday)	Average Crime Count (Weekend)
Alcohol Outlets	134	802	711	5.99	5.31
Bus Stops	38	398	251	10.47	6.61
Parks	62	571	471	9.21	7.60
Railway Stations	5	58	23	11.60	4.60
Schools	98	689	473	7.03	4.83
Shopping Malls	4	66	40	16.50	10.00

Table 8 compares the crime intensity results per facility type for weekday and weekend crime. During the weekday, shopping malls had the highest association with crime having roughly 17 crime incidents on average within a 50 metre radius.

Conversely, alcohol outlets had the fewest number of crime incidents per facility on the weekday, with approximately five incidents on average. The same was found for shopping malls on the weekend, with exactly 10 crime incidents on average. On the other hand, railway stations had the smallest average number of crimes with roughly four crime incidents per station. In summary, shopping malls were consistently the most associated with crime compared with the other five facility types regardless of the time or type of day. Alcohol outlets were commonly found to be least associated with crime during the daytime and during the week.

Tables 9 to 12 indicate the weights per facility type for daytime crime, night-time crime, weekday crime and weekend crime.

Table 9: Daytime crime intensity results

Facility Type	Average Crime Count	Conversion (0 – 1)	Multiply by 7	Add 1
Alcohol Outlets	4.72	0.10	0.67	1.67
Bus Stops	8.03	0.16	1.13	2.13
Parks	6.58	0.13	0.93	1.93
Railway Stations	8.40	0.17	1.19	2.19
Schools	5.57	0.11	0.79	1.79
Shopping Malls	16.25	0.33	2.30	3.30
Total	49.55	1.00	7.00	8.00

Table 10: Night-time crime intensity results

Facility Type	Average Crime Count	Conversion (0 – 1)	Multiply by 7	Add 1
Alcohol Outlets	6.57	0.13	0.92	1.92
Bus Stops	9.05	0.18	1.26	2.26
Parks	10.23	0.20	1.43	2.43
Railway Stations	7.80	0.16	1.09	2.09
Schools	6.29	0.13	0.88	1.88
Shopping Malls	10.25	0.20	1.43	2.43
Total	50.18	1.00	7.00	8.00

Table 11: Weekday crime intensity results

Facility Type	Average Crime Count	Conversion (0 – 1)	Multiply by 7	Add 1
Alcohol Outlets	5.99	0.10	0.69	1.69
Bus Stops	10.47	0.17	1.21	2.21
Parks	9.21	0.15	1.06	2.06
Railway Stations	11.60	0.19	1.34	2.34
Schools	7.03	0.12	0.81	1.81
Shopping Malls	16.50	0.27	1.90	2.90
Total	60.80	1.00	7.00	8.00

Table 12: Weekend crime intensity results

Facility Type	Average Crime Count	Conversion (0 – 1)	Multiply by 7	Add 1
Alcohol Outlets	5.31	0.14	0.95	1.95
Bus Stops	6.61	0.17	1.19	2.19
Parks	7.60	0.20	1.37	2.37
Railway Stations	4.60	0.12	0.83	1.83
Schools	4.83	0.12	0.87	1.87
Shopping Malls	10.00	0.26	1.80	2.80
Total	38.93	1.00	7.00	8.00

Table 13 compares the final weights calculated per facility for daytime crime, night-time crime, weekday crime and weekend crime, respectively.

Table 13: Weights per facility type for day, night, weekday and weekend

Facility Type	Weight (Day)	Weight (Night)	Weight (Weekday)	Weight (Weekend)
Alcohol Outlets	1.67	1.92	1.69	1.95
Bus Stops	2.13	2.26	2.21	2.19
Parks	1.93	2.43	2.06	2.37
Railway Stations	2.19	2.09	2.34	1.83
Schools	1.79	1.88	1.81	1.87
Shopping Malls	3.30	2.43	2.90	2.80

Shopping malls had the greatest weights for day, night, weekday and weekend, respectively. Alcohol outlets had the lowest weights for daytime and weekdays, whereas schools had the lowest weights for night-time and railway stations had the lowest for weekends, accordingly. These weights were all proportional to the relative crime counts per facility type.

Figure 31: Map comparing the safest routes (based on weighted polygon barriers) during the day, night, weekday and weekend, respectively, between the same two points in Khayelitsha

When these weights were used as inputs for the scaled cost values per barrier, it was found that all routes were identical (see Figure 31 above). These routes were all roughly 8.9 kilometres long and traversed 13 polygon barriers. These polygon barriers included five alcohol outlets, four bus stops, three schools and one park. This route also encountered some historical crime, namely, a total of 307 (n = 3.48 crime incidents per metre) and 392 (n = 4.17 crime incidents per metre) crime incidents during the day and night, respectively. The same route also came across a total of 414 (n = 4.22 crime incidents per metre) and 285 (n = 3.43 crime incidents per metre) historical crime incidents during the week and weekend, correspondingly. Despite the small changes in weights, the suggested route remained the same across day, night, weekdays and weekends.

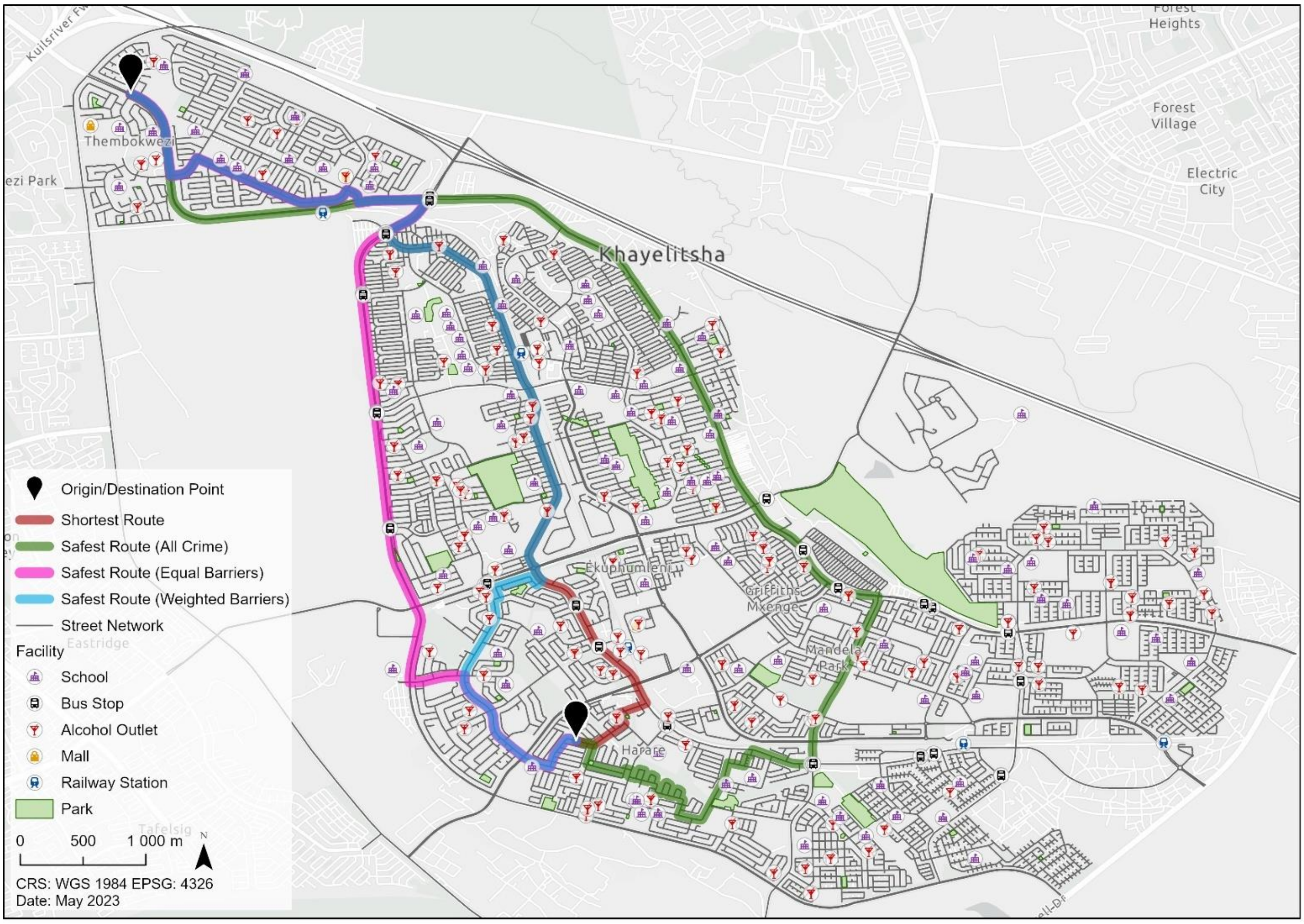

Figure 32: Map comparing all routes generated in this study between the same two points in Khayelitsha

Figure 32 compares the three methods employed to determine the safest walking route as well as the shortest route between the same random origin and destination point locations in Khayelitsha. The safest routes generated from Method 1, 2 and 3 are shown in green, pink and blue, respectively. With the shortest route represented in brown. The green route was most different to that of the other two safest routes and the shortest route, where only a handful of the same street segments were commonly traversed in the northern region of the township. The pink and blue route traversed the same street segments for the first and last section of the route, where they deviated in the middle of the route.

Table 14 illustrates the length (in metres), total historical crime count, total historical crime per metre encountered for the routes generated in Methods 1, 2 and 3 as well as the shortest route.

Table 14: Route results compared across all route types

Route	Length (m)	Crime Count	Crime Count per Metre
Shortest	8,370.35	735	7.60
Safest (Method 1: All Crime)	11,985.50	278	0.72
Safest (Method 2: Equal Barriers)	8,437.21	601	4.62
Safest (Method 3: Weighted Barriers)	8,897.77	699	7.65

The safest route between the origin and destination point is the longest route to travel at just under 12 km, however, this route encountered the least amount of crime with only 278 historical crime incidents (n = 0.72 crime incidents per metre). On the other hand, the safest routes in which risky facilities were considered, were much shorter. When risky facilities were assigned equal weights, the total length was roughly 8.4 km, and when they were assigned differing weights, the total length increased slightly to 8.9 km. The number of crimes encountered along the routes generated in Methods 2 and 3, were, however, quite similar, with the route from Method 2 having less historical crime incidents (601 crimes) compared with the route from Method 3 (699 crimes). The route with the weighted barriers (Method 3) encountered the highest total historical crime count per metre compared to all other routes with 7.65 crimes per metre.

Chapter 6: Discussion

This research study proposed three methods that could be employed to determine the safest walking route between two points in Khayelitsha, Cape Town. The choice between these methods is largely dependent on what data is available. If there is only historical crime data available, then Method 1 is most appropriate, on the other hand, if there is only data available for the locations of various crime generating facilities, then Method 2 is most appropriate. Lastly, if both historical crime data and 'risky facility' data are available, then Method 3 is most appropriate.

In Method 1, the safest route between the two origin and destination points was determined based on historical crime data (all types of crime occurring between 2012 and 2016). Not only was this done for all crime, but for daytime crime, night-time crime, weekday crime and weekend crime, in order to view the historical crime temporally. Each street segment was assigned a corresponding crime risk measure (i.e., number of crime incidents per metre) which was then used to determine the safest route. In this way Method 1 is similar to previous work done by Pang *et al.* (2019) who assigned a crime index (calculated based upon previous crime data) that represented the level of safety of a street segment in the United States. The work by Pang *et al.* (2019) differed slightly, however, whereby KDE was utilised to determine the crime index and real-time camera footage was further incorporated in the analysis. This research study is also comparable to Puthige *et al.* (2021) who modelled safe routes for users in New York. These researchers assigned a 'danger' value to each street segment in order to deter users from travelling along dangerous routes. However, this danger value did not only include historical crime data, but it also integrated an accident score and path length (kilometres). Moreover, the researchers weighted the severity of crime types, for example, rape was weighted far higher than theft, which was not considered in Method 1 of this research study. Other similar research includes Kim, Cha and Sandholm (2014) who designed a risky score per street based on Twitter feed data in Chicago and Lisowska-Kierepka (2022) who developed a criminal risk index per grid cell in Wrocław, Poland. The safe navigation application designed by Eckdale-Dudley *et al.* (2018) also determined safe walking routes, yet only considered road markings and quality of a street crossing when assessing street safety and disregarded historical crime data.

Elements of graph theory were also applied in this study where the Khayelitsha street network was regarded as a spatial graph with edges (street segments) and nodes (intersections). Within graph theory, edges are often assigned weights used to impede movement through a network, which in this case, was in the form of a crime risk measure (i.e., crime per metre) in Method 1 and street segment length (in metres) in Method 2 and 3. The 'law of crime concentration at place' moniker was shown to be true in the case of Khayelitsha as crime did indeed concentrate at certain street segments in the township (refer back to Figures 11 to 15 illustrating the results generated in Method 1). As shown previously, certain street segments had extremely high crime levels (more than 1.22 crime incidents per metre) while neighbouring street segments had far lower crime levels (0.006 to 0.033 crime incidents per metre). This clearly illustrates the spatial heterogeneity of crime along streets in Khayelitsha and highlights the importance of studying crime at such a micro-spatial level of aggregation. This heterogeneity could be due to the location of certain 'risky facilities' that attract criminal behaviour or other socio-economic characteristics of Khayelitsha that were not the focus of this study.

Regarding, daytime and night-time crime patterns from Method 1, only minor differences were found along Khayelitsha's street segments. The majority of the street segments had no crime throughout the township for both daytime and night-time indicating the high levels of spatial crime concentration at this level (see previous studies by Theron *et al.* (2022) as well as Breetzke and Edelstein (2019). The key difference was that there were slightly more street segments that experienced very high crime levels during the night than during the day. This could be due to the lack of activity on streets during the night and therefore less supervision and more favourable opportunities for crime, as per the routine activity theory. In terms of days of the week, crime patterns remained similar during weekdays and weekends. A few street segments had high crime levels and only a handful exhibited very high crime regardless of the day of the week. This means that there are certain streets that are more dangerous on a Saturday or Sunday, than during the week. These findings are similar to the ones by Oh *et al.* (2017) who learned that crime rates were higher on Fridays, Saturdays and Sundays.

When these crime measures (i.e., crime count per metre per time period) were used as travel impedances in the route analysis in Method 1, it was found that the safest route (considering all crime regardless of time/type of day) was somewhat longer (just under 12km) than the shortest route (roughly 8.4km). Despite the longer journey, the safest route successfully avoided several street segments that had many high crime incidents in the past and rather traversed street segments that posed less crime risk. The safest route encountered approximately 450 *less* crime incidents than the shortest route. This suggests that the shortest route traversed more street segments that had a far greater crime risk due to their past association with high crime levels. The safest route only encountered roughly 0.7 historical crime incidents per metre along the way whereas the shortest route encountered approximately 7.6 historical crime incidents per metre. That means that for every metre walked, a pedestrian would have experienced or been exposed to just over seven historical crime incidents along their journey down the shortest path. So, the importance of crime risk over walking distance influences the generated route between the origin and destination point locations.

Since the underlying crime patterns along street segments were very similar, it is not surprising that the safest walking route during the day did not differ much from the safest walking route at night. The routes only deviated from each other in some regions of the township, where the safest route during the day was roughly 600 metres shorter than the route during the night. Although these differences are minor, it still highlights the importance of reviewing the safest routes at different times of day. Undertaking similar analysis in another context could potentially indicate much greater differences in day- and night-time routes. Based on this study, however, it is clear that if pedestrians wish to walk during the night, they are advised to take a similar route as they would take during the day, at least for these two designed points used in this study. Nonetheless, even just avoiding a handful of street segments in the night can potentially save a pedestrian from experiencing serious crime. The same is true for the safest walking routes during the week compared to the weekend. Pedestrians are guided along a slightly different route during the week than during the weekend, where the latter is about one kilometre shorter in distance. The suggested safest route successfully reduced the total number of crime incidents traversed per metre during the week and disregarded the crime measures on the weekend. Ultimately, a slight difference in route choice can potentially make a big difference on pedestrian safety.

In Method 2, risky facilities were used when determining the safest routes between the origin and destination points. Recall that the term ‘risky facilities’ (see Eck *et al.*

2007) in this study refer to the six crime generators and attractors used in the analysis. In this method, 50-metre buffers were generated around various risky facilities and were used as polygon barriers for the route analysis. Freeways and offramps were also regarded as restriction line barriers and therefore completely avoided in the route analysis to ensure that pedestrians did not have to walk along these streets as they were perceived as being dangerous. Alfonso (2017) found the safest walking routes to schools in California and also incorporated polygon and line barriers in their analysis to indicate which streets were deemed as more dangerous. In their research, crime hotspots were converted into polygon barriers and then assigned a scaled cost of two so that any street that intersected with the crime hotspot was considered twice as dangerous than other streets that did not pass through the hotspots. This ensured that children took routes that avoided streets that had many crime incidents in the past and thus reduced the risk of crime they may have encountered on their journeys to school. Similarly, in Method 2 in this research study, all polygon barriers were assigned scaled costs of two which meant that any portion of a street segment that intersected with a polygon barrier was perceived as twice as unsafe as surrounding street segments. In this method, the geodesic length of the underlying street segments was set as the cost of travel. Therefore, the Route Analysis tool would always favour the shortest route that traverses the lowest number of polygon barriers since this was deemed as being safer, i.e., the less polygon barriers traversed, the safer the route.

When assigning all polygon barriers a scaled cost of two, the subsequent safest route between the two designated points had a total length of roughly 8.4 kilometres. Along this route, 12 risky facilities were traversed, including ten bus stops, one park and one school. So, although risky facilities were not avoided completely, this was still the safest route with the least exposure to these types of facilities in Khayelitsha. Along their walk, a pedestrian would have encountered approximately 5 historical crime incidents per metre.

Last, Method 3 combined the use of both historical crime incidents and risky facilities in order to determine the safest walking route between the two point locations in Khayelitsha. The historical crime data in this method was used to weight the risky facilities based on their corresponding prior association with crime. Method 3 is similar to the work conducted by Oh *et al.* (2017) who also considered the location and influence of facilities in their safe route recommendation method. They measured a crime rate per facility (based on five crime types occurring at these facilities) and then analysed how it influenced the crime risk of a route that passes through these facilities. They found that crime risk on a route increased when it passed/was in close proximity to high crime risk facilities. The research by Oh *et al.* (2017) does, however, differ from Method 3 in that crime risk per facility was measured by a value between one and ten (safest to most dangerous), rather than one and seven. In Method 3, for all crime, it was found that shopping malls had the greatest weight (2.86) followed by bus stops (2.20), parks (2.17), railway stations (2.13), schools (1.84) and lastly, alcohol outlets (1.79). Therefore shopping malls had the greatest association with crime which supports many anecdotal and academic studies that show how malls are often linked to crime across South African (Citizen Reporter 2022; Dayimani 2023; Gounden 2023; Hlangu 2023; Lindeque & Ntshidi 2021; McCain 2023; Modise 2023; Penny 2022; Phaliso 2023; Pijoos 2023; PropertyWheel_GLP 2018; Sefularo 2022; Seleka 2022) and other international contexts (Brantingham, Brantingham & Wong 1990; Ceccato *et al.* 2018; Mago *et al.* 2014; Peiser & Xiong 2020; Savard & Kennedy 2014). The fact that bus stops and railway stations were the second and fourth highest weighted facilities in this research study also support the results obtained by Breetzke and Edelstein (2022) who found that transport hubs can act as crime generators in Khayelitsha.

Based on Method 3, the safest route found between the same origin and destination point was 8.9 kilometres long. This route was considered the safest because it was the shortest route with the lowest crime risk (comparable to the bi-objective shortest path problem, called SAFEPATHS, by Galbrun *et al.* (2016) where crime risk and route distance were of equal importance). In this method, the route had to avoid as many highly weighted polygon barriers as possible while keeping the distance at a minimum. Consequently, along this route 13 risky facilities were encountered, of which five were alcohol outlets, four were bus stops, three were schools and one was a park. Alcohol outlets had the smallest weight when compared across all facility types and was therefore favoured over other types of facilities. The safest route generated in Method 2 passed ten bus stops whereas the safest route from Method 3 only passed four and this is due to their high weight.

The safest routes delineated using all three methods were all different. The shortest possible route between the two designated points had a total length of 8.37 kilometres while the safest routes generated in Method 2 and 3 were 8.44 kilometres and 8.90 kilometres, respectively. Although similar in length, the safest route from Method 2 encountered 134 *less* historical crime incidents in total than the shortest possible route while the safest route from Method 3 encountered 36 *less* historical crime incidents than the shortest possible route. The safest route determined in Method 1 was the longest route overall with a total walking distance of almost 12 kilometres. Despite the longer walk, this route only encountered a total of 278 historical crime incidents. Surprisingly, however, the safest route from Method 3 had the highest total historical crime count per metre when compared to all other routes. This route may have traversed a relatively short street that had a very high historical crime count that boosted this crime measure. So although this route had a lower total historical crime count than along the shortest route, it still had more crime incidents per metre.

The safest walking routes during the daytime, night-time, weekdays (Mondays - Fridays) and weekends (Saturdays and Sundays) were also determined in Method 3. The same process that was applied for all crime was applied to each time period as well. Each facility type was assigned a corresponding weight per time period which was subsequently used as the scaled costs for the respective polygon barriers. In the end, it was found that across all four time periods, the safest routes were broadly identical. This means that a pedestrian would walk the exact same safest route between the same origin and destination point regardless of time of day or day of the week.

Although not a central aim of the study, a spatial association was also found between crime and shopping malls (Button 2008; Lutchminarain 2012; Snyders & Landman 2018), transit facilities (Badiora *et al.* 2015; Brantingham & Brantingham 1993; 1995; Loukaitou-Sideris 2004; Natarajan *et al.* 2015; Stucky & Smith 2017; Xu & Griffiths 2017), parks (Groff & McCord 2012; Loukaitou-Sideris 2004) and schools (Breetzke & Edelstein 2022; Breetzke *et al.* 2021; Masitsa 2011; Murray & Swatt 2013; Roman 2002), respectively. This finding is supported by Breetzke and Edelstein (2022) who also found that schools, recreation hubs and transport interchanges act as crime generators in Khayelitsha. Their research findings showed that schools had the greatest intensity of crime, followed by recreation hubs and transport interchanges. In this study, it was found that shopping malls and parks had the greatest association with crime whereas alcohol outlets had the smallest association with crime.

Moreover, it was found that the intensity of crime near risky facilities varied temporally in Khayelitsha. In Method 3, it was found that during the daytime shopping malls were the riskiest (greatest crime intensity) while alcohol outlets were the least (lowest crime intensity) risky facilities. On the other hand, during the night-time both shopping malls and parks were deemed the riskiest while schools were the least risky facility types. During the week, it was also found that shopping malls had the greatest whereas alcohol outlets were least association with crime. On the weekend railway stations had the lowest average historical crime count, while shopping malls had the highest. Therefore, across all four temporal dimensions, shopping malls had the greatest average intensity of crime and was therefore most associated with crime. These patterns could be attributed to operating hours, for example, schools only operate during the daytime and during the week and therefore surrounding areas will have fewer crowds and heightened security during these time periods. Also, areas surrounding shopping malls could be deemed unsafe during the night because spaces such as parking lots stand open and unattended during the night and therefore create opportunities for criminal behaviour to occur. Furthermore, areas beside shopping malls during operating hours (i.e., during the day and throughout the week and weekends) can be crowded with a large pool of suitable targets, motivated offenders and lack of guardianship. Recall that according to the routine activity theory when these three elements converge at/near facilities such as malls (called activity nodes in the crime pattern theory) the risk of crime occurring increases.

The crime intensity near alcohol outlets, schools, parks and bus stops were also found to increase from day to night. This is supported by Schofield and Denson (2013) who found that as the opening hours of facilities change, the influence they may have on violent crime changes too. Furthermore, crime may worsen at night near certain types of facilities due to the social nature of these facilities and late operating hours. For instance, some facilities tend to get busier during the night and therefore create more opportunities for crime. Other types of facilities such as schools, parks and bus stops, however, typically become less busy at night which may reduce the likelihood of crime. Railway stations and shopping malls were the only two facility types that became less crime intensive during the evening. Both these facility types experience reduced activity at night than during the day which could explain this finding. It was found that all six facility types had a higher crime intensity during the week than on the weekend. As mentioned previously, shopping malls, for example, may have increased security on the weekends knowing there tends to be more visitors on a Saturday and Sunday which may prevent more crime from occurring. Also, during the week it could be that there are more commuters on busses and trains due to working hours typically being Monday to Friday, which creates a greater pool of motivated offenders and innocent victims. Routine activities such as traveling to work every day could help explain why more crime may occur near certain facilities during the week than on the weekend.

Both the routine activity theory as well as the crime pattern theory can help explain *why*, *when* and *how* crime occurs near these facilities and street segments. Certain street segments with bus stops positioned along them in Khayelitsha will experience large pools of commuters (i.e., suitable targets), inadequate security (i.e., guardianship) and a pool of motivated offenders who congregate around these facilities waiting for their bus to and from work. This in turn may create an ideal opportunity for crimes such as petty theft, and sexual harassment. According to the crime pattern theory, various types of facilities become activity nodes during peak hours when large crowds converge and the streets that connect these nodes form the cognitive map and awareness spaces, all of which become familiar to motivated offenders. These nodes and spaces form part of motivated offenders' comfort zones in which they are most likely to commit a crime. This also explains why certain risky facilities are more associated with crime than others (i.e., they have more activity and a greater opportunity for crime to occur).

As mentioned previously, graph theory was also applied in this research study whereby street segments were regarded as undirected edges and intersections were treated as nodes. Similar to previous studies of this nature, the geodesic length (in metres) of a street segment as well as its corresponding crime count per metre (i.e., crime risk) were attached to each edge and used as the costs of travel through the three proposed methods (see Galbrun *et al.* 2016; Kim *et al.* 2014; Lisowska-Kierepka 2022; Pang *et al.* 2019; Puthige *et al.* 2021). The fact that this research study in Khayelitsha focused on safe walking routes rather than safe driving routes also contributes to its novelty. The navigation methods and systems introduced by de Souza *et al.* (2019), Shah *et al.* (2011) and Puthige *et al.* (2021) were similar to the methods used in this Khayelitsha research study in that safety was considered when generating routes between origin and destination points. However, these previous studies focused on vehicular travel rather than walking, whereas Galbrun *et al.* (2016) and Alfonso (2017), on the other hand, did focus on walking as a mode of transport, but in an American context rather than a developing one.

This research study demonstrates the need as well as the impact of considering crime risk when running route analyses. Routes between the two origin and destination point locations differ greatly depending on the user preference, i.e., distance, crime risk or both. The three methods proposed in this study provide alternative ways to determine safe walking routes in Khayelitsha based on the data that is available. It considers three possibilities: only having historical crime data, only having the locations of risky facilities (found to be associated with crime) or having both historical crime data as well as the locations of risky facilities. The results from this study in Khayelitsha show that pedestrian safety can either be in terms of past crime records, the location of risky facilities or the combination of the two.

Practically, the three safe navigation methods introduced in this study can be used as a foundation for a mobile navigation application for individuals residing in Khayelitsha. This application will provide residents with an alternative to Google Maps or Waze specifically designed for safe walking in the developing context of Khayelitsha, similar to the online application created by Eckdale-Dudley *et al.* (2018) who helped parents find the safest walking routes to school in the US. Knowing which routes are safest to walk can also ensure pedestrians avoid street segments with a high concentration of historical crime or with many risky facilities located along them and in turn this will reduce the likelihood of them experiencing crime along their daily journeys. It is clear from the results of this study that the safest routes differ based on time of day as well as day of the week which is due to the heterogeneity of crime risk on adjacent street segments in Khayelitsha. Avoiding these individual risky streets can not only reduce an individuals' risk of criminal victimisation but also create opportunities for local authorities to improve the safety of high crime streets and facilities.

Practical implications

The findings of this research study should be used by the SAPS to direct patrol units to certain high-risk areas in an attempt to reduce the risk of crime. The crime intensity results near each facility type during the day and night can also help indicate exactly *where* and *when* additional patrolling units should be directed. The physical presence of police may put more pedestrians at ease knowing their walking routes are being policed. In fact, a similar approach was taken by the South African National Defence Force (SANDF) in 2019 who deployed troops (for up to six months) in an attempt to control the increasing gang violence in Khayelitsha by specifically targeting the known crime hot spots in the township. According to Sullivan (2020) these efforts did indeed reduce some crime in these hot spot areas. It is strongly encouraged that the local SAPS implement similar policing tactics in Khayelitsha in order to improve the safety of certain street segments and facilities in the township.

Local authorities can also ensure that high crime risk streets are physically improved by means of streetlights, camera surveillance, security guards, stewards and designated walking paths. Facilities such as parks should be regularly patrolled and well maintained to eliminate activities such as drug dealing and homelessness. Areas surrounding high risk facilities (such as shopping malls and parks in this case) should have permanent security staff and surveillance cameras to provide constant guardianship to help mitigate unwanted activity near these facilities during peak and off-peak hours. The physical environment of transit stops, such as bus stops and railway stations, should be maintained on a regular basis to ensure the quality of these facilities remain up-to-standard and do not attract any unsolicited activity.

There should be clearly marked walkways and roadway crossings near and around schools to ensure safe passage for school children as well.

The results from this research also show that it is sometimes inevitable that pedestrians will traverse some risky facilities and streets in order to get to their destination and therefore it is suggested that police officers/security guards be on standby in these areas to offer guardianship to pedestrians. In this way, a ‘guided walks’ initiative could be introduced so that if pedestrians feel unsafe in riskier areas, they can be accompanied by security personnel on their journey. This initiative has already been done at local universities, for example, and has helped students feel safer on their daily walks to campus. This is also similar to the ‘walking bus’ initiative in some Cape Town suburbs introduced by Muchaka (2012) whereby adult volunteers walk with groups of school children along certain routes to school to offer some guardianship and protection. Findings from Muchaka’s (2012) research showed that parents in both low income and higher income areas were willing to support this initiative. This initiative should be used in conjunction with the results found in this study which indicate the exact safest walking routes in Khayelitsha. As mentioned above, this initiative could be extended to offer women and other vulnerable community members (for example, elderly people) ‘guided walks’ throughout the township. This may help community members feel safer in their neighbourhoods knowing they have someone looking out for them.

These are just some precautionary measures that the SAPS, local authorities and private security companies can implement in order to eliminate and reduce crime risk along problematic streets in Khayelitsha. The key objectives of these safety measures are to ensure that there are fewer suitable victims, improved guardianship and in turn fewer motivated offenders which ultimately may reduce the risk of crime.

Chapter 7: Conclusion

Past studies have found that crime concentrates spatially (Breetzke & Edelstein 2019; Theron *et al.* 2023) in Khayelitsha with several facilities in the township also acting as crime generators (Breetzke & Edelstein 2022). Moreover, residents predominantly rely on walking as their primary source of travel in Khayelitsha which increases their risk of victimisation. These combined facts largely motivated this study, which aimed to find the safest walking route for pedestrians between two locations (origin and destination). In order to determine the safest walking route, three alternative methods were proposed. Method 1 made use of historical crime data, Method 2 made use of risky facility location data whereas Method 3 made use of both historical crime data and risky facility location data. The results from the three methods varied greatly, however, each route successfully reduced exposure to crime risk.

It is suggested that relevant stakeholders incorporate these three safe navigation methods into a mobile application so that users can receive safe walking routes between their inputted origin and destination points in Khayelitsha. The mobile application should provide users with additional preference settings such as specifying which risky facilities they wish to avoid completely or the maximum distance they are willing to walk while avoiding the riskiest street segments. Moreover, this research can be used as the foundation for a police patrol route optimisation application so that patrol routes (organised by SAPS or private security companies) can be better optimised and focused on certain high risk street segments within the township. This application could potentially suggest the most unsafe routes with the highest risk (i.e. most historical crime or risky facilities located along the way) as the main patrol routes.

It is also recommended that these three methods be applied to other geographical contexts and compared to the findings in Khayelitsha. Moreover, it is encouraged that up-to-date crime data be incorporated into Methods 1 and 3 for a more relevant/accurate representation of crime risk per street segment. Future work should also take a deeper look into the most appropriate method for weighting risky facilities based on their relative influence on street safety. In addition to this, facility operating hours should be incorporated in future work, especially with regards to Method 2 so that routes can be generated based on temporal filters. Future work could also compare the results of this research study with the perceptions of safety along these streets according to those who reside and walk in Khayelitsha. By means of a survey, one can better understand the true risk on these streets and test whether it correlates with the safest routes determined in this research (based on historical crime and the location of certain facilities).

Although this study filled a few research gaps, it is critical to acknowledge the limitations of the data used (discussed in the Data and Methods Chapter) and that this research study is highly context specific. It is important to note that the safest routes determined in this study are specific to the predetermined origin and destination locations, physical street network, historical crime incidents and position of risky facilities in Khayelitsha. Results will differ in different geographical contexts. Each method proposed also has its respective limitations. Method 1 does not consider the characteristics of the built environment (i.e. the location of facilities), while Method 2 does not consider true crime risk (i.e. crime data). All three methods also do not consider any socio-economic characteristics of Khayelitsha (such as population, age, income and gender).

Regardless of these limitations, this study represents the first empirical attempt to undertake a safest path analysis in any context in South Africa. Given the high rates of crime in the country, it is becoming increasingly important for individuals to know their risk of being victimised. For residents in Khayelitsha in particular, any information that can reduce their risk of victimisation is better than no information at all, regardless of the limitations. Hopefully, this study has addressed this in a small but meaningful way, and potentially introduce an application in the future which will give residents of Khayelitsha access to this vital information.

Chapter 8: References

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[i] Full list of all crime types included in this research study (as stated by SAPS): abduction, abduction (commen or statury law), any offence of an indecent nature against a female person not elsewhere specified, assault with the purpose to inflict grievous bodily harm, attempt; conspire; intice to commit sexual offence, attempted carjacking, attempted common robbery, attempted murder, attempted rape (not wife

by own husband - see code 02000-1) (only valid if committed before 2007-12-16 at 00:01), attempted robbery at business premises, attempted robbery at residential premises, attempted robbery with a fire-arm, attempted robbery with a weapon or instrument other than a fire-arm, business robbery, carjacking, common assault, common robbery, compel/cause persons 18 or older to witness sexual act, compelled rape, consensual sexual penetration with child between 12-16, expose/display genital organs/anus/female breasts to person 18 or older, expose/display of child pornography to person 18 or older, expose/display of child pornography/pornography to child, hijacking (truck), house robbery, immorality act (section 14 and 15) illicit carnal intercourse where there is no co-operating party, immorality act (section 14 and 15) illicit carnal intercourse where there is no co-operating party: carnal connection with, murder, murder of police official, other indecent; immoral or sexual offences not elsewhere specified, rape, robbery with a weapon or instrument other than a firearm, robbery with firearm, robbery with firearm – motor vehicle – cash in transit (transported by security firm), sexual assault, sexual exploitation of child.