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Author's Declaration

I hereby declare that I am the sole author of this dissertation. This is a true copy of the dissertation, including any required final revisions, as accepted by my examiners.

I understand that my dissertation may be made electronically available to the public.

Dedication

I would like to dedicate this project to my parents Mr. and Mrs. Mbano, my siblings Praymore, Trish and Nyasha; and not forgetting Lorreen Ranganai, Portia Gondo and Jonathan Mbano for their unwavering support during my five years of pursuing my first degree. Their support means my success beyond any doubt.

Abstract

This research presents an approach to examine the relationship between road traffic accidents and the environmental factors using spatial statistics. Road accident data for this research study was acquired from Leeds City Council database for the years 2009 to 2016.Other used datasets were obtained from OSM and DivaGis websites.

To examine spatial patterns of road traffic accidents in the city of Leeds, network kernel density estimation was used to determine the road accident hotspots for reported accidents. The results revealed that some road segments have higher accident rates compared to some road segments that never had even a single reported road accident since 2009 to 2016. Ordinary Least squares technique was conducted to test the relationships between the dependent variable (road traffic accidents) and independent variables (retail outlets, recreational areas, public areas, liquor outlets and street furniture). Moran's I statistics was used to assess for spatial autocorrelation in the datasets. The result of this research show that the proximity of retail outlets, recreational areas, public places, liquor outlets and street has a strong correlation with the number of road traffic injury incidents.

Acknowledgements

The bible says in Zechariah 4:6, "…, its not by might, nor by power, but by my spirit, said the LORD of hosts" . I thank God who gave me the opportunity, skills and strength to sail through this project. It is not by my wisdom nor strength that I managed to complete this project, but it is by the grace of the Almighty God. I would also like to thank my supervisor Dr. P.T Makanga who guided me throughout the course of this research.

Finally, it is my pleasure to thank my parents and family for their unlimited support and my friends for their support. I pray that the Almighty God bless them abundantly.

Table of Contents

List of Tables

List of Figures

CHAPTER 1: Introduction

1.1 Background of the Study

In recent years, the number of studies about the tools for analysing accidents and road design has increased considerably. Among these tools, Geographical Information Systems (GIS) stand out for their ability to perform complex spatial analyses (Gholam Ali Shafabakhsh et al., 2017). However, sometimes the GIS, has been used only as a geographical database to store and represent data about accidents and road characteristics. It has also been used to represent the results of statistical studies of accidents, but these statistical studies have not been carried out with GIS. Owing to its integrated statistical-analysis capabilities GIS provides several advantages. First, it allows a more careful and accurate data selection, screening and reduction. Also, it allows a spatial analysis of the results in pre-processing and post-processing. Secondly, GIS allows the development of spatial statistics that rely on geographically-referenced data (Romi Satria and María Castro, 2016) .The non-random distribution of accidents, both in time and space, raises questions about the location and the reasons for those accident location (Schuurman et al., 2009). Understanding the spatial patterns will help the analysts and local authorities to make a better decision about protecting the environment.

Accident/Collision as anything that happens suddenly on roads leading to personal injury occurring on the public roads (including footways) in which at least one road vehicle is in collision with another vehicle or a vehicle in collision with a pedestrian is involved and which becomes known to the police within 30 days of its occurrence (Jean Siakeu, 2015). One accident may give rise to several casualties and the victims of Road accidents are not restricted to people travelling in cars, public transport or heavy vehicles but also include pedestrians, cyclists and two wheelers (R.Shad et al.,(2013);Syed Ibrahim Kabeer, 2016).

Danger of accidents

The increase in motorization creates more traffic interaction among the road users, including pedestrians, therefore causing serious road safety problems. (V. Prasannakumar et al., 2011). A significant unexpected outcome of transportation systems are road traffic accidents which provides significant social and economic losses (Thakali, 2016 and Annette Prüss-Ustün et al., 2016). External road transport costs include effects of traffic accidents, which forming about 2.5% of gross domestic product of the European Union countries (Dean Brabec et al., 2011).Road traffic accidents are claiming the lives of millions of people, and causing destruction of property leading to social and economic crisis of households (Micheale Kihishen Gebru, 2017). Based on the 2015 World Health Organisation report, the worldwide road traffic deaths reach 1.25 million people per year with many more injuries and damage to infrastructure, (WHO, 2015). By 2050, 66% of the world's population will live in urban areas, which are often characterized by more traffic thus increasing the road traffic volume hence higher chances of accident occurrence.(Annette Prüss-Ustün et al., 2016).

To ensure healthy lives and promote wellbeing for all ages, Sustainable Development Goals 2030 section 3.6 is aiming to reduce global deaths and injuries from road traffic accidents by 50% as of the year 2020 (United Nations, 2015).As many studies indicated road traffic accident by 2020 is expected to be the third major killer and largest leading cause of death and disabilities after perinatal as shown in the table below. (World Health Organization, 2013,Micheale Kihishen Gebru, 2017).

Table 1. Rank order of disease burden of disability adjusted life years (DALYs) for the ten leading causes of the global burden of disease from 1990 to 2020. Source: (World Health Organization, 2013)

Rank	Leading cause of disease or injury in 1990	Rank	Leading cause of disease or injury by 2020
1	Lower respiratory infections	1	Ischemic heart
2	Diarrhea	2	Unpopular major depression
3	Perinatal	**3**	**Road traffic crashes**
4	Unpopular major depression	4	Cerebrovascular
5	Ischemic heart	5	Pulmonary
6	Cerebrovascular	6	Lower respiratory infections
7	Tuberculosis	7	Tuberculosis
8	Measles	8	War
9	**Road traffic crashes**	9	Diarrhea
10	Congenital Anomalies	10	HIV

Table 1: Report on road traffic injury prevention

Road accidents are a major issue of concern since they lead to the damage of infrastructure, environment, vehicles, injuries, and loss of life at a greater extent (Satria and Castro, 2016). The impact it causes on human, physical and financial capital is huge. Road traffic accidents also affect national development efforts directly or indirectly because it leads to loss of the economic active population and human costs is usually adds grief to the overall estimate of Road traffic accidents costs. (Brussels, 2007).For the accident survivors, there is not only lost working time to consider, but also reduced income after resuming employment thus disadvantaging those who are dependent on them. Some of those injured will not return to their jobs, and will spend additional time looking for new employment. (Dorota Masniak, 2007 ; Matthew James Kittelson, 2010;and Micheale Kihishen Gebru, 2017) .

1.2 Purpose of the study

Currently, the United Nations goals includes halving number of global deaths and injuries from road traffic accidents by the year 2020 (United Nations, 2015). The issue of road traffic accident is worthy of investigation, because the human security threat of road traffic accidents has not been fully recognized, and has not been well studied as compared to other threats of human security such as HIV/AIDS and violent political conflicts, though it is one of the most frequent causes of human death and loss of properties (Micheale Kihishen Gebru, 2017).One of the best ways to reduce road traffic accidents is by rectifying the road traffic accident causes. Identifying hazardous roads locations and investigating their association with the social and environmental risk factors will be very helpful in identifying road traffic accident root-causes.(Ghazan Khan et al., (2008); Kuhlmann et al., 2009); Lalita THAKALI et al., (2009); (Dai et al., 2010; R.Shad et al.,(2013); Luciano de Andrade et al., 2014 Thakali et al.,(2015) ; Seiji et al., (2015); Himalaya Singh et al., (2016); Jeremy. M. Bundi (Dr.) et al., (2017)).

Problem definition

Past studies demonstrated the use of a few non-parametric methods in road accidents modelling without their applications in road safety analyses such as identification of specific road accident hotspots (Lalita Thakali, 2016).There is a possibility that social or environmental correlates exist with the road accident hotspot region but are simply not yet identified by researchers.(Blake Byron Walker and Nadine Schuurman, 2015).The non-random distribution of road accidents, both in time and space, often raises questions about the location and the reasons for that location but all the reasons are not yet known.(Schuurman, N et al., 2009; V. Prasannakumar et al., 2011).Based on the collected accident data of reported road accidents from 2009-2016, the city of Leeds has a record of 21 429 accidents which involves pedestrians, cyclists and motorists. Of those accidents the 1% of victims were involved in fatal injuries, while 11% were seriously injured and 88% were slightly accidents.

1.3 Main objective

This study shall investigate how much the environmental factors surrounding road traffic accidents, influence in the occurring of road accidents in a city environment using Spatial statistics techniques.

1.4 Specific objectives

1. Mapping traffic accidents distribution in a city
2. Examine the relationship between road traffic accidents and the environmental characteristics.

1.5 Justification

To reduce traffic accidents and improve road safety, it is crucial to understand how, where and when traffic accidents occurred. An improved understanding of spatial patterns of traffic accidents can make accident reduction efforts more effective and easy. For instance, knowing where and when traffic accidents usually occur, helps law enforcement can conduct more efficient patrols and roadway departments can disseminate more effectively to drivers the critical information about roadway conditions

1.6 Research Outline

The research shall concentrate on applying Geomatics to map road traffic accidents distribution around the city, thus showing riskier road segments. Based on literature environmental characteristics that may be suspected to be related with road accident shall be mapped using geospatial methods. Spatial analysis tool and spatial statistics tools shall be used to examine if the mapped environmental factors are contributing towards road accidents and to what extent.

In conclusion, the research shall concentrate on applying spatial analysis tool to identify risky road segments. This study shall investigate the environmental factors surrounding road traffic accidents, and how much they influence in the occurring of road accidents in a city environment using Spatial analysing techniques. This shall be carried out considering City of Leeds as a case study.

CHAPTER 2: Literature Review

2.1 Mapping traffic accidents distribution in a city

An important application of injury epidemiology is to identify the prone geographical areas and the population groups that are at high risk of injury or death based on reliable data sources or statistics (Lightstone et al., 2001). Based on the oxford dictionary, injury epidemiology is the branch of medical science dealing with the transmission and control of diseases. One of the most critical questions that traffic safety engineers face is where to implement safety countermeasures, such that the most significant impact on safety can be achieved. The accurate identification of safety deficient areas on a broader scale for planning purposes and on a local scale for road safety treatments is the key to a successful and comprehensive road safety program.(Ghazan Khan et al., 2008).

Targeted, place-based interventions could help reduce road traffic accidents because certain geographic areas experience much higher numbers of road traffic accidents than do most other areas due to the unknown reasons which this study is interested in looking at. (Kuhlmann et al., 2009). Hotspots, which are defined as relatively high-risk locations, are commonly identified on the basis of some specific selection criteria (Thakali et al., 2015).Traffic accident density estimation enable the determination of dangerous areas objectively and easily as it indicated where area-wide traffic calming can be implemented preferentially. (Seiji et al., 2015).

In a study to locate areas that are prone to child pedestrian to motor vehicle collisions in Long Beach city, Lightstone et al., (2001) used geographic information system (GIS) software to locate the spatial distribution of road accidents. The kriging and Idw models are considered as desirable models for estimating accidents, as it will show that some areas represent the most probability of accident occurrence.(R.Shad et al., 2013).

In addition, (Atsuyuki Okabe et al., 2008) did a road accident analysis in which the road accident distribution was done using Network Kernel Density Estimation methods which provided better results for network related data as compared to Normal kernel density estimation. Produit Timoth´ee et al., (2008) chose Network Kernel Density Estimation (NetKDE) over Normal Kernel Density Estimation, because NetKDE seems to be more proficient in highlighting linear clusters oriented along a street network as it operates by extending the bandwidth distance along the street network rather than linearly across the space.

Luciano de Andrade et al., (2014) used spatial analysis by finding road accident hotspot points using a combination of Kernel Density Estimator and Wavelet Analysis to identify the main hotspots for road traffic accidents in the Brazilian roads. In a study for identifying crash hotspots in a road network, Thakali et al. (2015) compared the two geostatistical-based approaches, namely kernel density estimation (KDE) and kriging, and found that kriging techniques are the promising perspective for road safety analysis even though KDE overweighed Kriging because it takes into consideration of spatial autocorrelation of crashes. In a study to identify features of the built environment that correlate with areas of high violent injury incidence, Walker and Schuurman, (2015) used Kernel density estimation to identify hotspots. To efficiently assess the road accidents distribution, Seiji et al.,(2015) used Kernel density estimation (KDE) techniques and concluded that the bandwidth significantly affects the results, thus moderate bandwidth should be used. To identify the high density road segments and intersections for accidents occurrences, Dai et al. (2010) did a comparison between network-based Kernel Density Estimation (NetKDE) and ordinary Kernel Density Estimation, and found the NetKDE performing better.

KDE is a function balancing events accordingly to their distances and required two parameters. The first is the bandwidth, which is the distance of influence and the second parameter is the weighting function *K*, which is most often a normal function (Produit Timoth´ee et al., 2008). The application of the ordinary two-dimensional kernel method to density estimation on a network produces biased estimates; in particular, it overestimates the densities around nodes (Atsuyuki Okabe et al., 2008).Network Kernel Density Estimation (NetKDE) perform better than the ordinary Kernel Density Estimation (KDE), which confirms previous findings by literature.

NetKDE has a similar mathematical formula as KDE, but the difference being that distances are measured along a network rather than Euclidean distances to compute density values as done by KDE. The normal KDE creates a continuous space which is too strong for the analysis of events which take place in a one-dimensional sub-space created by a network such as road accidents. Nevertheless, the NetKDE operates by extending the bandwidth distance along the street network rather than linearly across the space as done by normal KDE.(Atsuyuki Okabe et al., 2008; Dai et al., 2010; Produit Timoth´ee et al., 2008).

According to (Atsuyuki Okabe et al., 2008) , the formula for network kernel density estimation is shown below:

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{r} k\left(\frac{d_{is}}{r}\right) \tag{2.1}$$

Equation 1: Network Kernel Density Estimation Formula

Where $\lambda(s)$ is the density at location s, r is the search radius (bandwidth) of the KDE (only points within r are used to estimate $\lambda(s)$), k is the weight of a point i at distance d_{is} to location s

As shown in the figure below, around each feature point (the accident), the KDE method draws a circular neighbourhood and then a mathematical equation is used ,that goes from the position of the feature point up to the neighbourhood boundary.(Gholam Ali Shafabakhsh et al., 2017; Zhixiao Xie and Jun Yan, 2008)

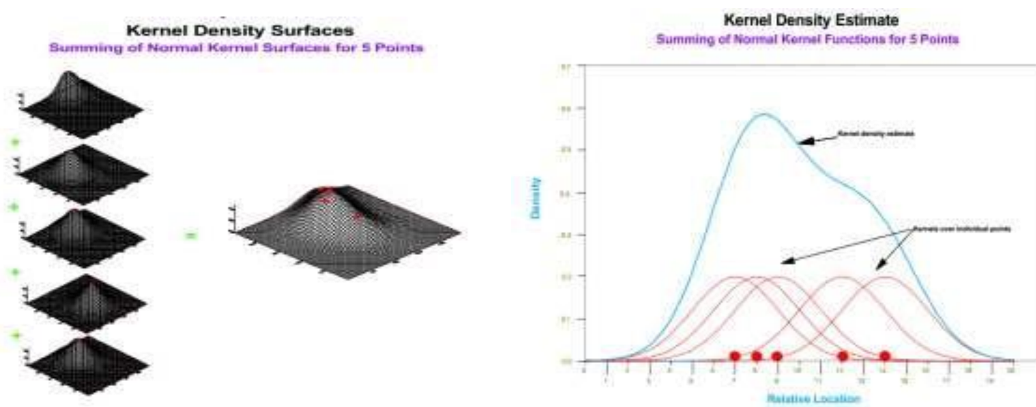


Figure 1:Kernel Density Estimation Surface

One of the attractive parts of the NetKDE method as compared to other methods of clustering is that it takes into consideration of spatial autocorrelation of crashes. KDE is a non-parametric approach hence it does not involve an estimation of the parameters of a statistic. (Thakali et al., 2015). Since KDE is a nonparametric method, its main advantage is that it is a specification free approach (Lalita Thakali, 2016). Ke Nie et al., (2015) and Plug, C. et al., (2011) added that, KDE is better for visualization purposes than for identification of black spots because it necessary to decide which clusters are statistically significant to the hotspot, nevertheless, there is not enough attention paid to the statistical significance of KDE in the current literature (Ke Nie et al., 2015).

Advantages and disadvantages of different spatial pattern analytical tools and clustering tests

Spatial Pattern/ Clustering Test	Advantage	Disadvantage
Moran's I or Geary's C	Provide comparison among smaller portions of the area, can be standardized. Variations exists for testing autocorrelation at the local level.(Lalita Thakali, 2016)	Issues with specifying the optimal weight to be used in the calculation of Moran's I; seems to work better when there is little spatial dependence in the data.(Lalita Thakali, 2016)
Gi* statistic	Estimates density distribution of events at the local level; allows assessment of spatial association in a study area or of a observation; and identifies statistically significant hotspots/cold spots	Clusters composed of few observations may inflate Gi* although other methods that allow the selection of only the most robust clusters is available
Standard deviation ellipses	Size and shape of ellipses provides easy visualization of differences in point dispersion	Large areas defined by ellipses are not very informative for prioritizing intervention areas; clusters may not follow an elliptical shape, and thus any interpretation maybe incorrect
Kernel density estimation	KDE is a non-parametric approach hence it does not involve an estimation of the parameters of a statistic. (Lalita Thakali, 2016) It takes into consideration of spatial autocorrelation of crashes.(R.Shad et al., 2013) KDE is good for visualization purposes. (Ke Nie et al., 2015; Plug, C. et al., 2011)	User must specify grid cell, bandwidth and thematic threshold, thus prone to error. Based on the PAI (prediction accuracy index) measure, the kriging method outperformed the KDE method in its ability to detect hotspots. (Thakali et al., 2015) It operates by extending the bandwidth distance across the space rather than along the street network. (Produit Timoth´ee et al., 2008) Nevertheless, there is not enough attention paid to the statistical significance of KDE in the current literature(Ke Nie et al., 2015)
Kriging	Based on Prediction Accuracy Index, the kriging method outperformed the KDE method in its ability to detect hotspots. Better in handling spatially auto-correlated datasets. (Thakali et al., 2015) We could use it to relate environmental factors to hotspots provided the data for the factors is geocoded (Thakali et al., 2015)	Poor for visualization purposes. (Ke Nie et al., 2015; Plug, C. et al., 2011)
Network Kernel density estimation	More proficient in highlighting linear clusters oriented along a street network as it operates by extending the bandwidth distance along the street network rather than linearly across the space. (Produit Timoth´ee et al., 2008)(Ke Nie et al., 2015; Plug, C. et al., 2011)	Nevertheless, there is not enough attention paid to the statistical significance of KDE in the current literature(Ke Nie et al., 2015)
Getis-Ord	Measures a single value of the spatial correlation and provides a measure of the clustering degree value in the spatial pattern.(Romi Satria and María Castro, 2016) Ability to discriminate between hot spots and cold spots (Praprut Songchitruksa and Xiaosi Zeng, 2010) The *Gi** statistics method can tell if the accident of reference lies in the cluster of high/low values	The computational resource required can be demanding when the sample size gets large. (Praprut Songchitruksa and Xiaosi Zeng, 2010)

Table 2:Advantages and Disadvantages of different Spatial pattern analytical tools

2.2 Mapping out the environmental characteristics on road accident scenes

For every road accident that occurs, it involve the person, machine(vehicle) and the environment ,which comprises of the natural and man-made features, (Jeremy. M. Bundi et al., 2017).Based on the most public health researches, it is evident that features of neighborhood environments are associated with health behaviours and outcomes (Yen-Cheng Chiang et al., 2017 and Jeremy. M. Bundi et al., 2017).

Mapping out the environmental characteristics on road accident scenes is very useful as it helps us to understand the surrounding features that may elevate risk for traffic accidents. Mapping out the environmental characteristics on road accident scenes is made possible as GIS has that potential to integrate complex data on spatial variation of events to identify significant associations between anomalies or "hot spot", with geographic areas requiring further fieldwork, analysis, or education outreach, or to direct and monitor policy to areas of greatest need. (Lightstone et al., 2001).The possible environmental characteristics that correlate to the incidents such as violent injury, road accidents, robberies etc. can be culled from a detailed literature review.(Blake Byron Walker and Nadine Schuurman, 2015).

To access that information of the environmental characteristics of the surrounding area one can use methods primary data collection method (visit physically) , secondary data (use already available spatial data) , or use of remote sensing techniques (acquiring data from a remote location) (Ian Heywood et al., 2006). Geographical maps are one best ways to get data from, as it is easier to visually examine aspects of locations not captured by variables observed directly (Lightstone et al., 2001). The environmental scan can also be done by physically visiting the scenes and recording the important features wanted on the hotspots. (Badland et al., 2010 ; Blake Byron Walker and Nadine Schuurman, 2015).

In contrast to the methods of doing an environment scan as stated above, technological advancements are providing opportunities to examine the neighbourhood streetscape remotely because there is an increasing recognition that the neighbourhood-built environment influences health outcomes, such as physical activity behaviours ,(Badland et al., 2010). In a study to assess levels of agreement between computer-based and on-site auditing Griew et al., (2013) recommended the use of Google Street View to capture street characteristic data and considered it as an efficient method that could substantially increase potential for large-scale objective data collection. In a study to check if virtual Streetscape audits can reliably replace physical streetscape audits, virtual audits methods thrived when the streetscape were conducted by the same researcher using Google Street View software versus the physical survey done for the same geographic locations for comparison reasons ,(Badland et al., 2010).

The Google Street View tool was found to have pros and cons even though the pros overbalanced the cons. The main limitations are that: Firstly, there is no full information such as the building's purpose may not have been clear and any pedestrian and cyclist "cut-through" that would enhance the legibility of the neighbourhood would be harder to detect using remote means. Secondly, we cannot have all the information on google street view.eg land use etc. unless when available, objectively derived (GIS) measures of land use mix and street connectivity should be used to accurately assess these variables. Thirdly, the limitation of Google Street View as a research tool is the time lapse between the recording of the street imagery and the physical audit date. (Griew et al., 2013; Badland et al., 2010;Luciano de Andrade et al., 2014).

The ease, speed, safe approach, low associated costs, efficiency, convenience and high criterion reliability of desk-based auditing are argued to considerably out-weigh their limitations. Additionally, the findings from these studies indicated that desk-based audits using Google Street View provided an effective and reliable alternative to in-person street audits within the developed countries including the UK. Desk-based auditing vastly improves the potential for analysis across diverse areas within countries and internationally. These findings demonstrated that Google Street View was the best tool to measure the streetscape context at the neighbourhood level as it outweighed other traditional methods that had been used.(Griew et al., 2013;Badland et al., 2010;Luciano de Andrade et al., 2014 and Yen-Cheng Chiang et al., 2017).

2.3 Examining the relationship between road traffic accidents and the environmental factors

It is encouraged by the Epidemiologic investigation to recognize the factors that lead to an increase in risk that is not necessarily the same in all population groups; and also with the aim of providing an insight into potential effects of environmental factors on RTCs and to improve preventive measures (Lightstone et al., 2001 and Kamran B Lankarani et al., 2014).Based on previous studies ,it is clear that environmental factors appear to be associated with road accidents and they do have an amplifying effect on accident risk(Luciano de Andrade et al.(2014) ,Dai et al.(2010) ; Kamran B Lankarani et al., 2014 and Yen-Cheng Chiang et al., (2017)). In support ,Badland et al.(2010) added that there is increasing recognition that the neighbourhood-built environment influences health outcomes, such as physical activity behaviours, and technological changes.

Kuhlmann et al., (2009) clearly shows that each area with a specific land use has a specific level of risk on road accidents, because each land use attracts different types of people thus it influences the number of the people in that area, hence directly affecting the rate of occurrence of incidents such as road traffic accidents, violent injuries etc. The findings of the study suggested that violent injury is a geographically complex phenomenon related the built environment. In addition, Jeremy. M. Bundi et al., (2017) deduced that both natural and manmade environmental factors are major causes of road accidents.

In order to verify patterns contributing to crash occurrence in the hotspots built environment analysis and Principal component analysis were conducted and that helped in identifying five different patterns demonstrating that specific environmental characteristics are associated with different types of fatal crashes,(Luciano de Andrade et al., 2014).

Geostatistical techniques such as universal kriging method can be applied to identify if these factors make significant contribution to Hotspots of road accident events over a geographical space, (Thakali et al., 2015).Based on R.Shad et al.(2013) Kriging and IDW models are considered as desirable models for estimating accidents, as they describe the concepts relating to accident distribution operators, together with theoretical fundamentals and the necessary formulas. The factors were obtained by analysing weight of each layer in accident-prone points. Blake used the Vancouver Area Neighbourhood Deprivation Index (VANDIX) to classify injury hotspots, and test the association between injury and social deprivation.

To explore the spatial pattern of weather-related crashes, specifically crashes related to rain, fog, and snow conditions Ghazan Khan et al., (2008) used Getis-Ord Gi statistics. (Kuhlmann et al., 2009) used a Global Moran Index calculation from the studentized residual of the linear regression model to indicate remaining spatial correlation in the linear mode. V. Prasannakumar et al., (2011) assessed spatial clustering of accidents and hotspots spatial densities following Moran's I method of spatial autocorrelation, Getis-Ord Gi* statistics and point Kernel density functions. Regression analysis is used to understand, model, predict, and/or explain complex phenomena, examining if a certain factor or factors have a contribution to the outcome of the incident. In a study to investigate Spatial-Temporal Clustering of Road Accidents V. Prasannakumar et al.,(2011) used Global Moran's I spatial autocorrelation test for each type of accident incidence in the area. In addition, a hot-spot analysis and Kernel density estimation were also carried out based on the Getis-Ord Gi* statistics and point Kernel density function.

Ordinary Least Squares

Spatial autocorrelation is also used to explore the association between two variables (Kuhlmann et al., 2009); and after obtaining it, the next step in the process is to evaluate relationships between two or more feature attributes using regression such as Ordinary Least Square regression. Ordinary Least Squares (OLS) linear regression generates predictions or models a dependent variable in terms of its relationships to a set of explanatory variables. OLS provides a global model of the process one is trying to predict or understand; and finally creating a single regression equation to represent that process.

Global Moran's I

To be able to measure the relationship among features according to their spatial arrangement, it is necessary to conduct spatial autocorrelation. Global spatial autocorrelation identifies whether the values of a variable show a significant pattern of regional clustering.(Vaz, E. and Khaper, M, 2016).In global measures, the relationship among features may be described as positive correlation if similar values are spatially close to each other (clustered), negative correlation if different values are located near one another (dispersed) and random if spatial pattern cannot be distinguished from the arrangement of values (Getis A, 2008).In order to understand and measure such pattern, statistical tools such as Moran's I can be used to measure the dispersal or clustering of the features in space. (A Rukewe et al., 2014; Kuhlmann et al., 2009).

The Spatial autocorrelation (Moran's I method), works not only on feature locations or attribute values alone but on both feature locations and feature values simultaneously (V. Prasannakumar et al., 2011). Moran's I is one of the oldest indicators of global spatial autocorrelation, it measures based on both their values and spatial locations of features (Kuhlmann et al., 2009). It compares the value of the variable at any one location with the value at all other locations (V. Prasannakumar et al., 2011).

Global Moran's I results includes the Moran's I Index value and both a z-score and p-value that are used to evaluate the significance of that Index. For a known distribution, the numerical approximations of the area under the curve are P-values and these are limited by the test statistic.The results of the Spatial Autocorrelation (Global Moran's I) analysis are always interpreted within the context of its null hypothesis which states that the attribute being analyzed is randomly distributed among the features in the study area. (A Rukewe et al., 2014; Kuhlmann et al., 2009).

For no spatial pattern in the data, Moran's, I have an expected value of –[1/(n-1)]. For a positive spatial autocorrelation, values of **I** should exceed –[1/(n-1)] and a negative spatial autocorrelation, is indicated by the values of I which are below the expectation. The calculated value of I should be equal to the expectation, which will be in the limits of statistical significance, if the yi is independent of the values of yj, j (and J is the set of neighbouring locations). As the number of locations increases, the expectation for an ordinary correlation coefficient approaches zero . (Eduardo S. Almeida et al., 2003).The following equation is for the Moran Index as supported by Eduardo S. Almeida et al., (2003) and A Rukewe et al., (2014).

$$I = \frac{n}{\sum\sum w_{ij}} \frac{\sum\sum w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum (y_i - \bar{y})^2}$$

Equation 2:Moran's Index formula

Where **n** is the number of locations, **Yi** is the data value of attribute in analysis (in our case, accident rate), **Wij** is a spatial weight for the pair of locations **i** and **j**.

2.4 Related Work

R.Shad et al. (2013) found that accident occurrence is affected by the environmental factors such as area of intersection, width of passage, length of streets, bus stations and land use. Luciano de Andrade et al., (2014) added that, sectors with high incidence of fatal pedestrian crashes were associated with higher length of road in urban area, limited lighting, more double lane roads, lower frequency of auxiliary lanes, the absents of a traffic light and smaller curve rate were associated with higher risk of fatal crashes with vehicles. Kamran B Lankarani et al., (2014) found that, roadway environmental factors included crash scene light, weather conditions, place of accident, the defects and geometrics of roadway and road surface had an influence on the occurrence of road accidents.

Jeremy. M. Bundi (Dr.) et al., (2017) found that, the odds of injury were higher in dusty weather and lower in foggy, snowy, rainy and cloudy weather than the clear weather. He also added that accidents mostly occur on broader roads than narrower ones and found that there is also a relationship between seasonality; weather and time factor in road traffic accident shows that street width, street condition, furniture zone, and street furniture are positively associated with pedestrian crashes.

(Dai et al., 2010) also added that there is also a correlation between pedestrian crashes and road infrastructure such as street furniture, furniture zone, street condition and also the street width as there is a higher frequency of road accidents in road segments with strong street compactness and also mixed land use present. Mixed land use, such as a mixture of residential areas with commercial and retail businesses was found to have an influential role in pedestrian safety, as they attract foot traffic around the businesses. In those mixed land use, Kuhlmann et al., (2009) found that the main variables that could lead to road traffic accidents are, liquor license outlets, land use, sociodemographic factors and pedestrian activity.

The environmental characteristic associated with road accidents based on literature are summarized in the table below:

Name of factor	**Authors**
Alcohol service	(R. Shad et al., 2013); (Kuhlmann et al., 2009)
width of passage	(R.Shad et al., 2013); Jeremy. M. Bundi (Dr.) et al., (2017)
length of streets	(R.Shad et al., 2013); (Luciano de Andrade et al., 2014)
Bus stations	(R.Shad et al., 2013); Jeremy. M. Bundi (Dr.) et al., (2017)
Mixed land usages	(R. Shad et al., 2013); (Dai et al., 2010); (Kuhlmann et al., 2009)
Accident scene lighting	(Luciano de Andrade et al., 2014); Kamran B Lankarani et al.,(2014);
more double lane roads	(Luciano de Andrade et al., 2014)
lower frequency of auxiliary lanes	(Luciano de Andrade et al., 2014)
The absents of a traffic light	(Luciano de Andrade et al., 2014)
Weather conditions	Kamran B Lankarani et al.,(2014); Jeremy. M. Bundi (Dr.) et al., (2017)
Roadway defects and geometrics	Kamran B Lankarani et al., (2014)
Road Surface	Kamran B Lankarani et al., (2014)
Time	Jeremy. M. Bundi (Dr.) et al., (2017)

Table 3:environmental characteristic associated with road accidents

2.5 Knowledge gaps

Past studies demonstrated the use of a few non-parametric methods in road accidents modelling without their applications in road safety analyses such as identification of road accident hotspots.(Lalita Thakali, 2016)

It is possible that social or environmental correlates exist with the road accident hotspot region but are simply not yet identified by researchers.(Blake Byron Walker and Nadine Schuurman, 2015).

The non-random distribution of road accidents, both in time and space, often raises questions about the location and the reasons for that location but all the reasons are not yet known.(Schuurman, N et al., 2009; V. Prasannakumar et al., 2011).

In conclusion, Network Kernel Density shall be used for mapping road accident hotspots. Thus, the NetKDE shall be used for visualisation purposes, to show the riskier road segments in the city. For the sake of mapping the environmental factors that are to be investigated, there is no need to physically visit all the accident sites because there is an option for accessing that information, by secondary data collection methods. To investigate the relationship between the environmental factors and accident locations, Ordinary least squares shall be used and Moran's I used to measure spatial autocorrelation. The study shall investigate accidents that happen between day and night, and examining their relationship with the following factors: Retail outlets, Recreational areas, Public areas, liquor outlets and street furniture.

CHAPTER 3: Methods

3.1 Mapping traffic accidents distribution

Leeds City Council published the spatial data for road accidents that happened in period of 8 years (2009 to 2016) and that data was obtained from: https://data.gov.uk/dataset/road-trafficaccidents .To visualise the road accident hotspot over the network space, the SANET add-on for ArcGIS Desktop (versions 10.0) was used. A 100m search radius was used for the network kernel density analysis.

3.1.2 Mapping Environmental factors

Data on the environmental characteristics related to the occurrence of traffic accidents was created using secondary data collection methods. The data for roads, Liquor outlets, retail areas, public places, street furniture, and recreational areas were obtained from OpenStreetMap website at https://www.openstreetmap.org/export#map=11/53.8226/-1.5454&layers=H .The data for the city of Leeds general administration boundary was obtained from DIVA GIS website at :http://www.diva-gis.org/datadown.

3.2 Examining the relationship between road traffic accidents and the environmental factors

Based on spatial location, the road network density estimation surface was joined to the density surface of the factors to be investigates (e.g. liquor outlets density, recreational area density etc.) all in vector form. Using ordinary least squares spatial statistics tool, the road accidents distribution density is the dependent variable and the explanatory variables are the density estimation surfaces for factors to be investigated on influencing the occurrence of road accidents. The explanatory variables are Liquor Outlets density surface, Retail outlets density surface, street furniture density surface, Recreational places density surface and Public areas density surface. After running the Ordinary Least Squares tool, one of the outputs are the Standard Residuals which are then analysed for spatial autocorrelation using the Moran’s I spatial statistics tool in ArcGIS 10.2.

The density estimation for environmental factor (e.g. liquor Outlets) are obtained using Kernel density estimation. The output raster file is converted to vector by using raster to point tool and the output is joined using the spatial join based on spatial location. The output is a vector shapefile containing the columns of density estimation for accidents and the other for liquor outlets distribution. As shown by the figure below.

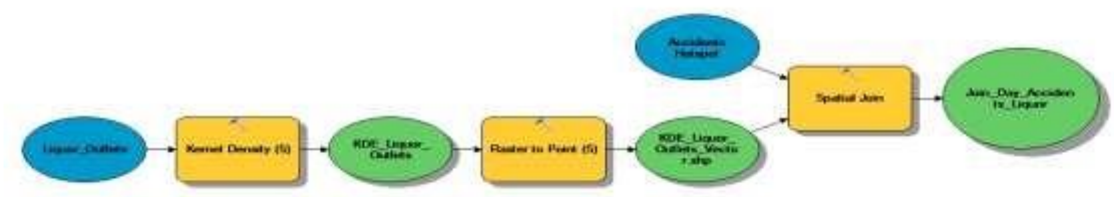


Figure 2:Density estimation model for environmental factors

The Joined shapefile containing the columns of density estimation for accidents and liquor outlets distribution is analysed using Ordinary Least Squares and the output will produce the Standardized Residuals that are run in the global Moran's I spatial statistics tool to test for spatial autocorrelation.

Global Moran's I: If the values in the dataset tend to cluster spatially (high values cluster near other high values; low values cluster near other low values), the Moran's Index will be positive. When high values repel other high values, and tend to be near low values, the Index will be negative. If positive cross-product values balance negative cross-product values, the Index will be near zero. For no spatial pattern in the data, Moran's, I have an expected value of –[1/(n-1)]. For a positive spatial autocorrelation, values of **I** should exceed –[1/(n-1)] and a negative spatial autocorrelation, is indicated by the values of I which are below the expectation. For all scenarios, the z values are greater than 1.96 meaning that there is a spatial autocorrelation at 95% significant level thus the outcome is not a result of random distribution.

Adjusted R-squared: Tells how much of the variation in the dependent variables is accounted for by the independent variables. Ranges from 0 (the independent variables are not related to the dependent variable) to 1 (the independent variables explain all variation in the dependent variable).

Coefficient: They are values, one for each explanatory variable, that represent the strength and the type of the relationship the environmental factor to the occurrence of accident, holding all other variables constant. In regression with a single independent variable, the coefficient tells how much the dependent variable (Road accidents) is expected to increase (if the coefficient is positive) or decrease (if the coefficient is negative) when that independent variable (environmental factors) increases by one.

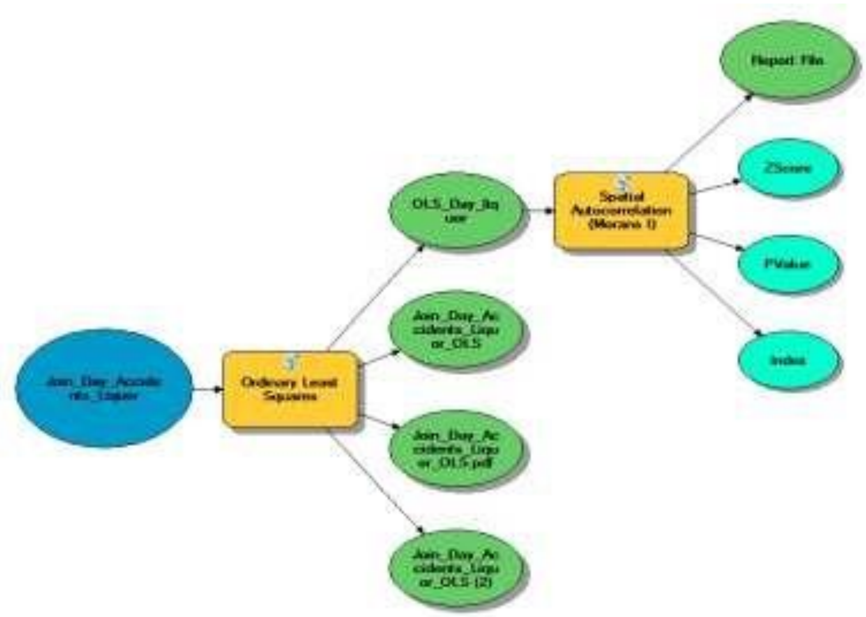


Figure 3:Ordinary Least Squares and Moran's Index

CHAPTER 4: Results

4.1 Traffic accidents distribution

Mapping road accidents

The map below shows the reported 21 429 road accidents from the year 2009 to 2016 in the city of Leeds. The road accidents are mainly concentrated at the centre of the City of Leeds city.

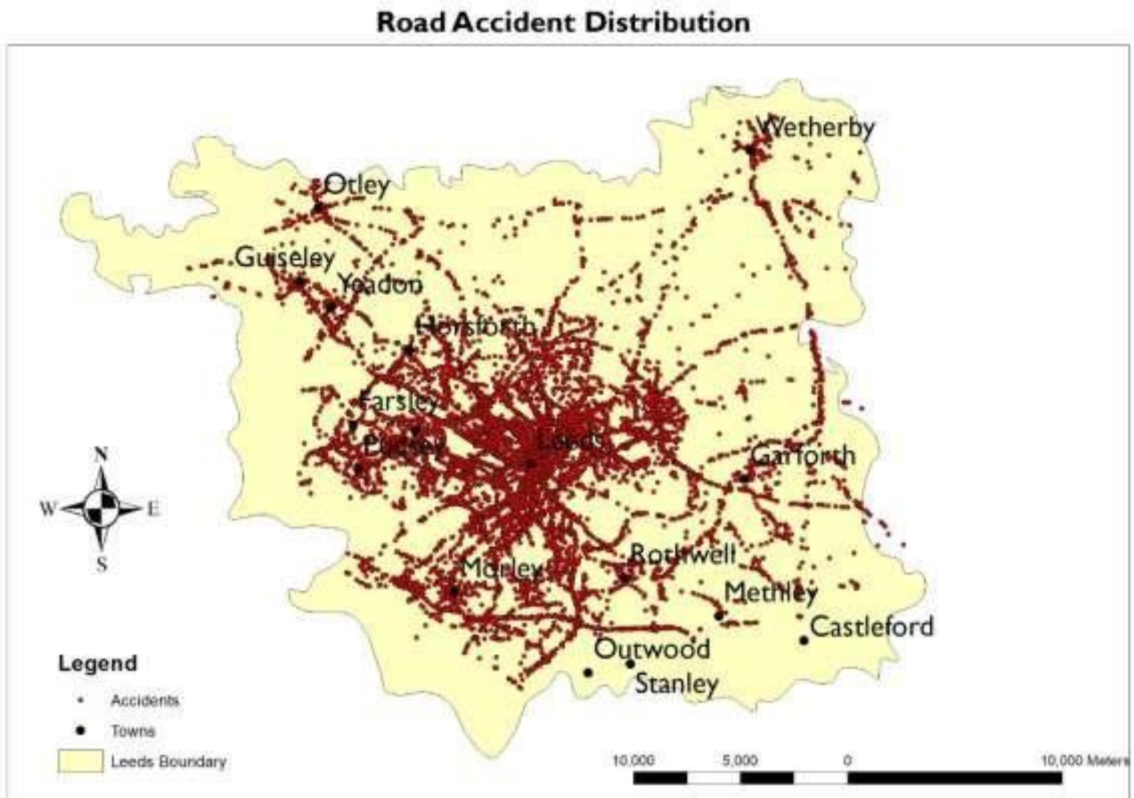


Figure 4: Road accidents

Road accident distribution

Based on the results, there are some road segments that have more road accidents than others even if they are close together. The map below shows the distribution of road accidents based on network kernel density estimation method, where red segments shows road accident prone segments (High value of road accident density) and green segments show safer roads in which there are few or no accidents records at all (Low value of road accident density).

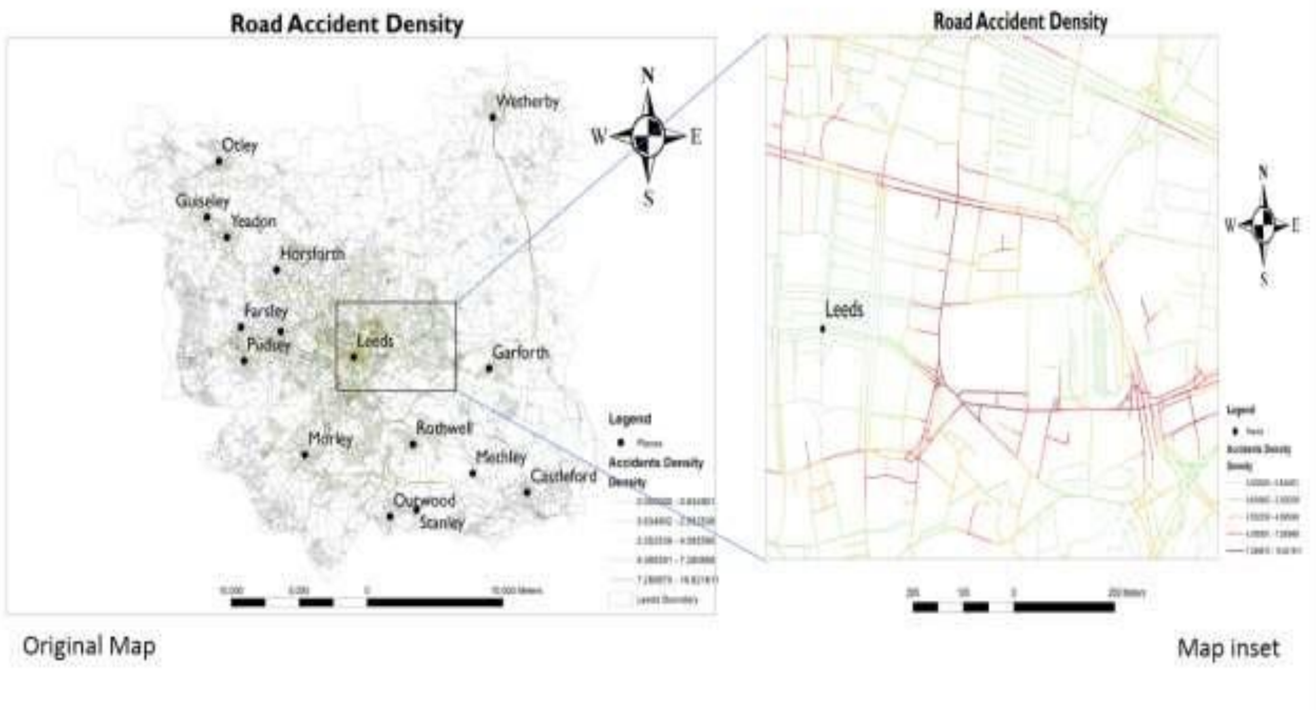


Figure 5: Road accident network based density

The density distribution of City of Leeds is also shown in the figure below. Based on the results, some areas show high density of road accidents per square km. The highest being 891 accidents per square km at the city centre and is at city center and the least is zero. The map below shows accident distribution density where darker areas shows accident prone areas (High value of road accident density) and lighter area show few or no accidents records at all (Low value of road accident density).

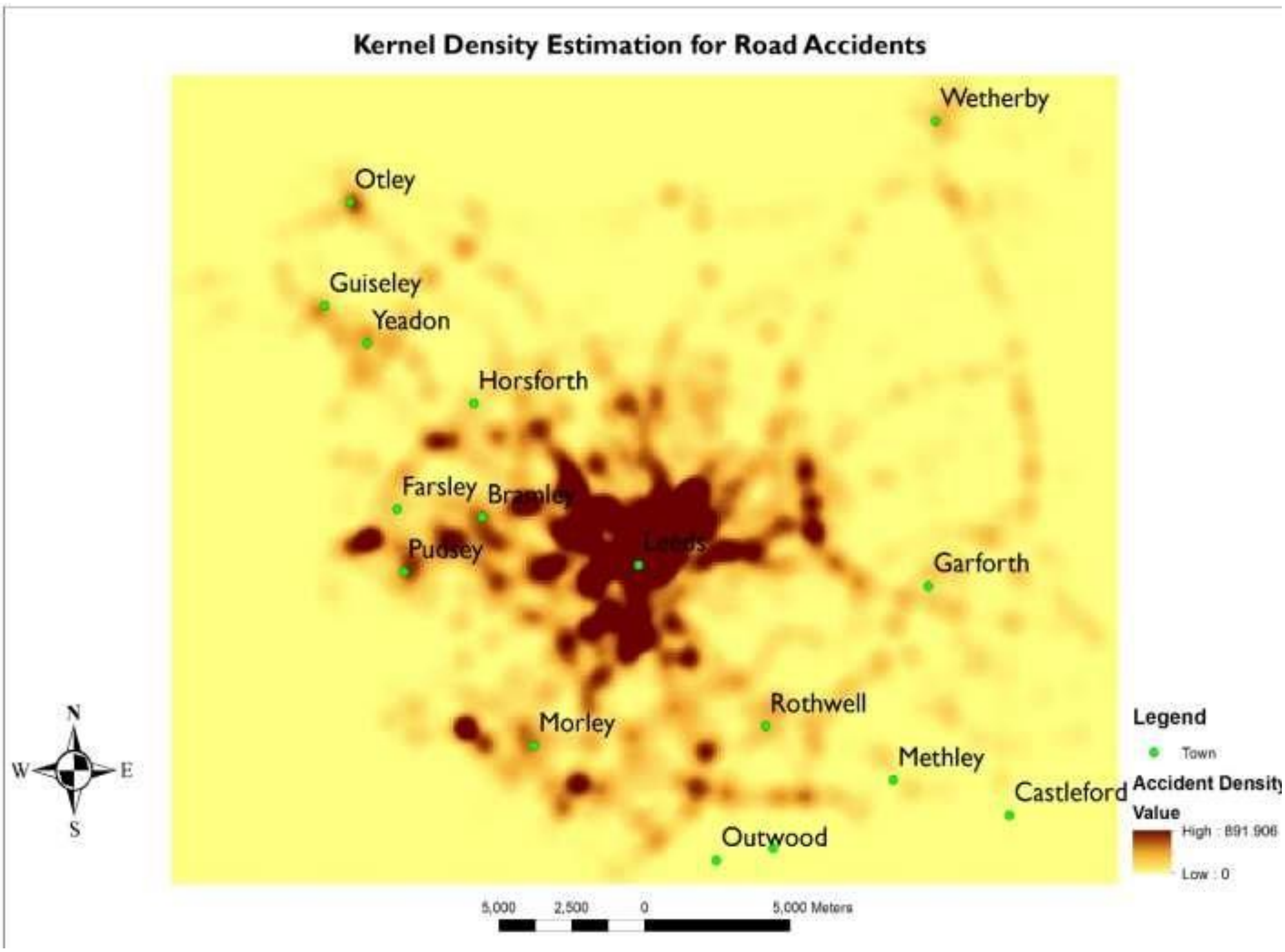


Figure 6: Road accident Kernel density surface

4.1.2 Environmental factors

Map **A** shows the retail outlets that are in the city of Leeds, this class includes bicycle rental shops, saloons, jewellery shops,kiosk,outdoor shop,mall,shoe shop , supermarket, vending machine, sports shop and toy shop.Map **B** is showing the public areas that are in the city of leeds,the public areas contain town halls, theatre, telephone, convenience (public toilet), community centre and public buildings.Map **C** is showing the recreational areas that are in the city of leeds and it is made up of archaeological sites , arts centre, artwork, monument,museum, park,picnic site, ruins and view points.Map **D** shows the liquor outlets that are in the city of leeds,this includes night clubs,bars and pubs.Map **E** shows street furniture in the city of leeds,this includes mobile phone shop, drinking water locations,street benches,mobile fast food outlets and busstops.

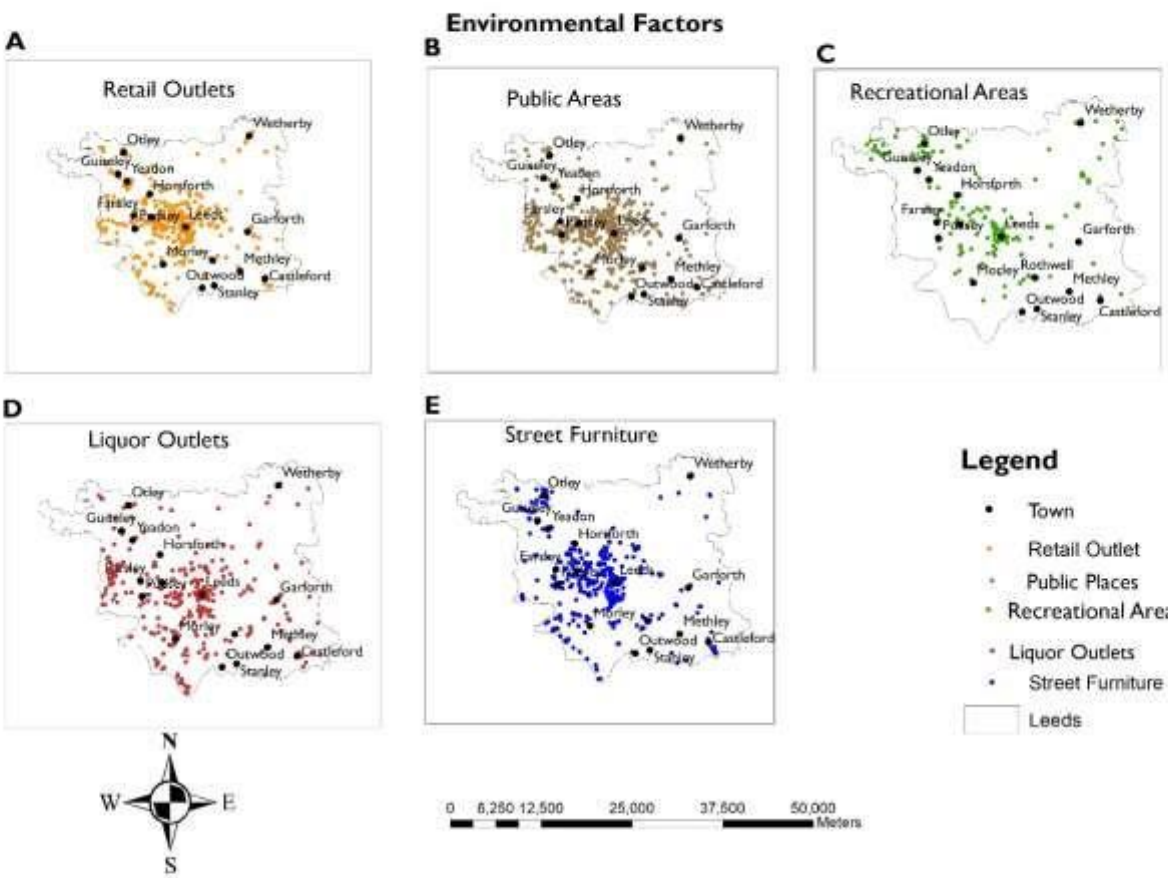


Figure 7: Environmental factors

Density distribution of environmental factors

Diagram **A i**s a map showing the density distribution of retail outlets where the highest is showing 122 Retail Outlets per square kilometer. Map **B** shows the density distribution of public places where the highest density is 28 public places per square km. Map **C** shows the density distribution of recreational areas where the highest density of 3 recreational areas per square km. Map **D** shows the density distribution of liquor outlets where the highest density is of 26 liquor outlets per square km. Map **C** shows the density distribution of recreational areas where the highest 3 recreational areas per square km. Map **E** shows the density distribution of street furniture in the city where the highest density is 35 street furniture units per square km.

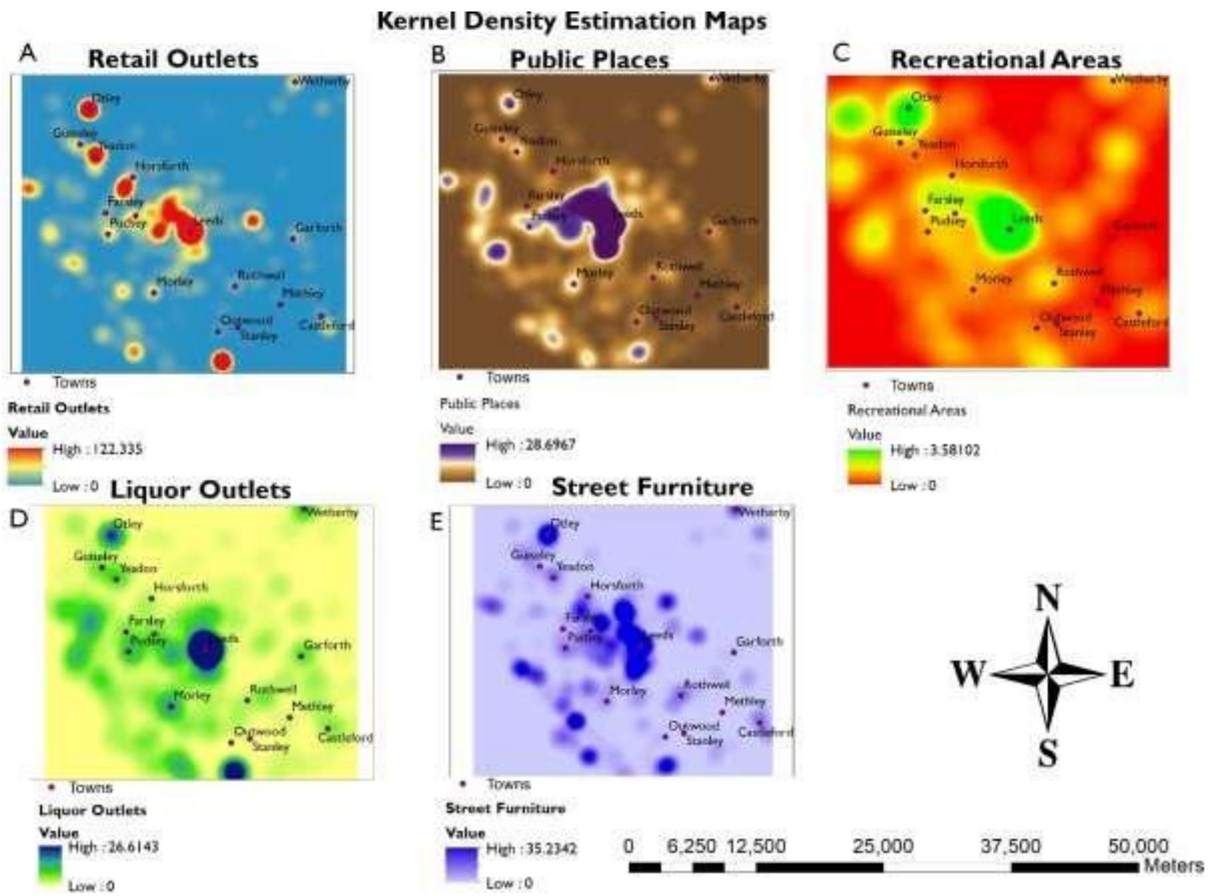


Figure 8: Environmental factors Density Estimation

4.2 Relationship between road traffic accidents and the environmental characteristics

For day accidents, the expected index value for spatial clustering of all environmental factors and the road accidents is equal to -0.000011. All environmental factors tested for autocorrelation resulting in a Moran's Index value greater than 0.981212 and this indicates a positive spatial autocorrelation. This shows that high values of accident density cluster near other high-density values of environmental factors and low values of accident density cluster near other low values of environmental factors density. For night accidents, the expected index value for spatial clustering of all environmental factors and the road accidents is equal to -0.000012. All environmental factors tested for autocorrelation, resulting in a Moran's Index value greater than 0.991559 and this indicates a positive spatial autocorrelation. This shows that high values of accident density cluster near other high-density values of environmental factors and low values of accident density cluster near other low values of environmental factors density.

For retail outlets, the model explained approximately 43.05% of the variance in density of road accidents during the day and 48.70% for the night. The relationship between road accidents distribution and recreational areas indicates 44.30% of the variance in density of road accidents during the day and 49.61% during the night. For public areas, the model explains 52.34% and 59.77% of the variance in the density of road accidents during the day and night respectively. Liquor outlets effects on road accident density shows, that the model explains 44.43% and 49.31% of the variance in the density of road accidents during the day and night respectively. Street furniture positively influence the occurrence of road accidents by 40.76% and 36.85% during the day and night respectively.

When retail outlets increase by 1, road accidents increase by a factor of 5 during the day and increase by 2 during the night. Increasing the recreational areas by 1, will increase the road accidents rate by a factor of 73 during the day and 30 during the night. An increase with 1 public facility will result in the increase in road accidents by a factor of 15 during the day and factor of 6 during the night. For liquor outlets, an increase by 1 will result in an increase in road accidents by a factor of 17 during the day and 7 during the night. An increase in 1 in street furniture will result in the increase in road accidents by a factor of 10 during the day and factor of 7 during the night.

Day Accidents (6:00am-5:59pm)

Factor	Moran's I	Expected I	Z value	Adjusted R^2	Coefficient
Retail Outlets	0.985074	-0.000011	410.422	0.430555	+5.082155
Recreational areas	0.983184	-0.000011	409.624	0.442990	+ 73.512323
Public areas	0.981212	-0.000011	408.829	0.523376	+ 15.071329
liquor Outlets	0.983699	-0.000011	409.846	0.444296	+ 17.397843
Street Furniture	0.986059	-0.000011	410.833725	0.407645	+10.079229

Table 4: Day road accidents

Night events (6:00pm-5:59am)

Factor	Moran's I	Expected I	Z value	Adjusted R^2	Coefficient
Retail Outlets	0.994175	-0.000012	409.003	0.487028	+2.117580
Recreational areas	0.992374	-0.000012	407.95	0.496136	+ 30.584991
Public areas	0.991559	-0.000012	407.965	0.597729	+ 6.316852
liquor Outlets	0.993208	-0.000012	409.107	0.493059	+7.184838
Street Furniture	0.994466	-0.000012	409.110	0.368469	+7.184838

Table 5: Night road accidents

CHAPTER 5: Discussion

Firstly, past studies demonstrated the use of a few non-parametric methods in road accidents modelling without their applications in road safety analyses such as identification of network based road accident hotspots.(Lalita Thakali, 2016).In this research, Network KDE has been used to really identify the exact road segments with much road accidents in a road network.

Secondly, one of the knowledge gaps identified in the literature review was that it is possible that social or environmental correlates exist with the road accident hotspot region but are simply not yet identified by researcher. In addition ,the non-random distribution of road accidents, both in time and space, often raises questions about the location and the reasons for that location but all the reasons are not yet known.(Schuurman, N et al., 2009; V. Prasannakumar et al., 2011, Blake Byron Walker and Nadine Schuurman, 2015).To address the second knowledge gap, this research investigated on the following environmental factors: retail outlets, street furniture, recreational areas, public places and liquor outlets. The significance of the research is that the non-random distribution of road accidents, both in time and space for the city of Leeds, has been explained by the positive spatial autocorrelation of the environmental factors and the accidents hotspots.

The results accuracy may have been affected by locational errors since some accidents happened in bad weathers that may affect the locational position accuracy and multipath of GNSS signals in the city environment. The results could have been affected by missing data because the recorded road accidents data only shows reported road accidents as declared by the data source (City of Leeds Metropolis) that not all accidents are not reported. The data for environmental factors does not reflect the actual environmental condition at time of accident thus chances are that some features may have changed hence the data used may be inaccurate.

CHAPTER 6: Conclusion

6.1 Findings

This research shows that there are some accident risky road segments, that are associated with more traffic accidents compared to others. The detection helps to identify vulnerable locations and road segments that require remedial measures. Through this work, it has been confirmed that there is spatial association between road accidents and suspected features of the built environment from the literature. In addition, the non-random distribution of accidents, both in time and space, is a result of the investigated environmental features which are, but not limited to retail outlets, recreational areas, public areas, liquor outlets and street furniture. An increase in any of the investigated environmental factors will result in an increase in rate of accidents during the day more than it does during the night.

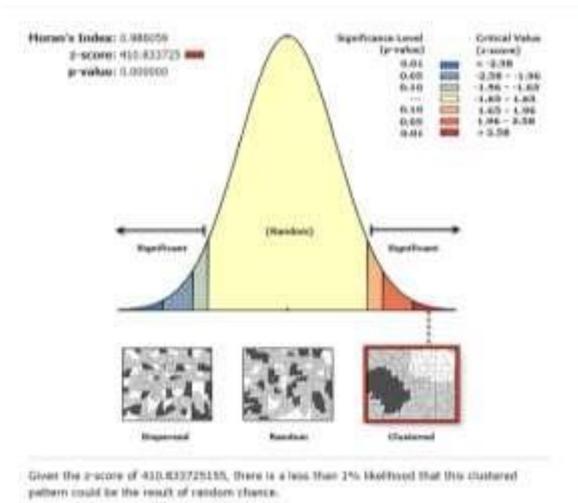
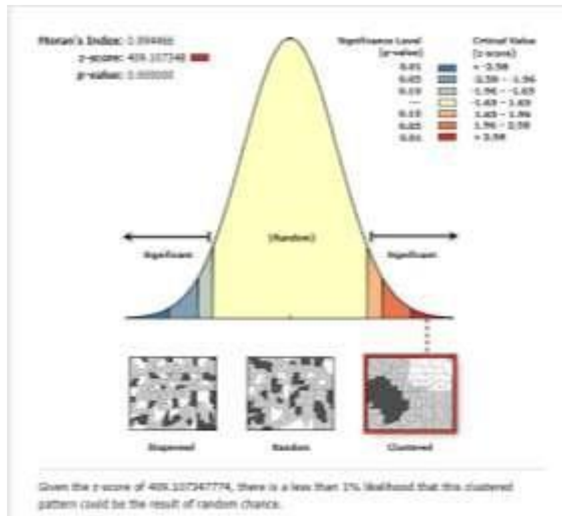
6.2 Limitations

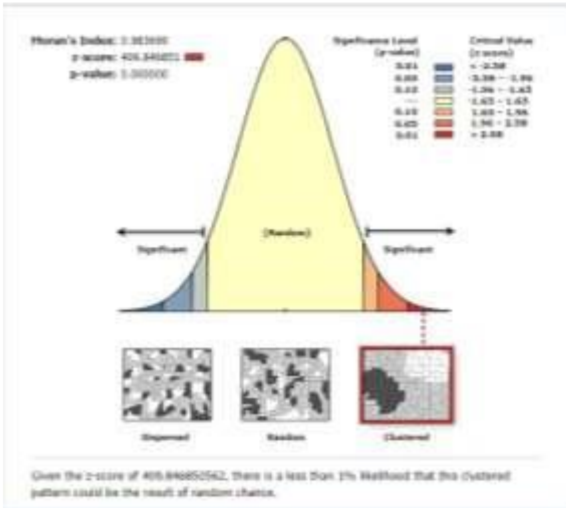
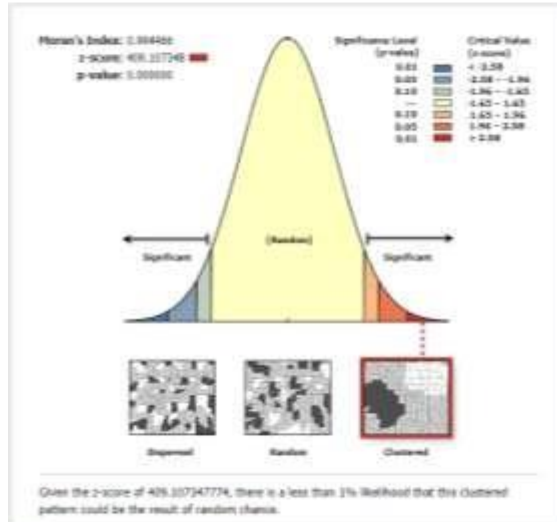
The certainty of the network Kernel Density Estimation tool as developed by SANET group has not yet been known because it has not been reviewed by much research as it is being used as an experiment. The road accident data include only reported road accidents meaning that, the data is not up-to-date as some of the incidents are may not be reported as declared by the data source (City of Leeds). The accident data source does not guarantee for data accuracy as some of the data were collected in poor weather conditions and at times poor internet connectivity. The data accuracy is not known thus it’s a limit when one wants to use the same data for an analysis that needs higher data accuracy. The mapped environmental features were last updated in August 2017 form OSM, but there is no record showing exactly what surrounding environmental factors were present during time of road accident occurrence, thus the analysis may not have been based on highly accurate data. There may be more environmental factors that may be missing in the literature which need to be examined for their effect on the occurrence of road accidents for example: graffiti, crime rate, religion, lifestyle of people around the accident scene etc.

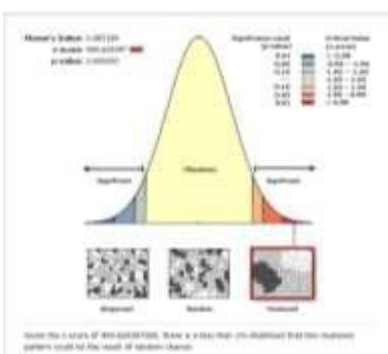
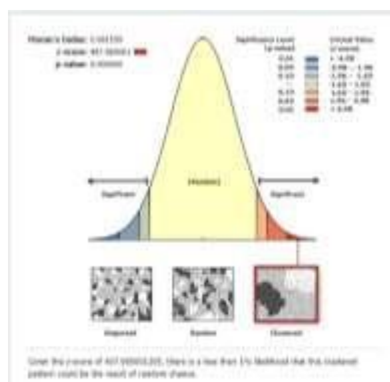
6.3 Recommendations

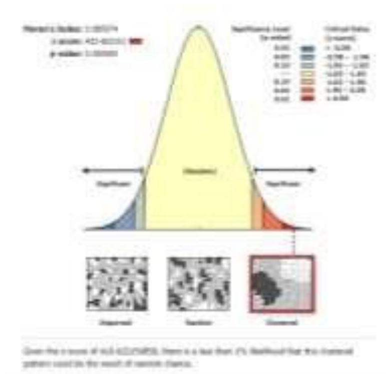
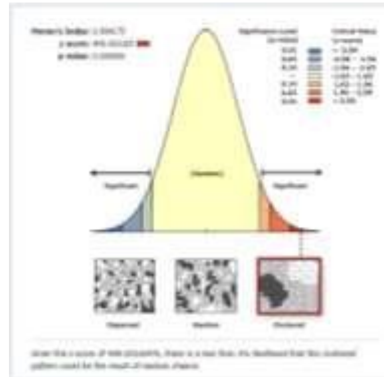
Local authorities who are responsible for recording road accidents, should use geospatial data collection methods such as handheld GNSS instruments. When the accident data is being collected, an environmental scan should be conducted, thus recording environmental factors around accident scene. More ways of road accident data collection should be used, such as using drones and terrestrial photogrammetry.

Appendix

<table>
<tr><th>Day Accidents</th><th>Night Accidents</th></tr>
<tr><td>Street furniture
</td><td>Street furniture
</td></tr>
</table>

Liquor outlets 	Liquor outlets 

Day Accidents	Night Accidents
Recreational areas 	Recreational areas 

Retail outlets	Retail outlets
	

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