STUDY OF THE EFFECTS OF BUILT ENVIRONMENT ON PEDESTRIAN CRASH FREQUENCY AND SEVERITY IN DHAKA

by

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April, 2022

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Niaz Mahmud Zafri

I dedicate this thesis to my beloved wife

ACKNOWLEDGEMENT

I start in the name of Allah, the most gracious, the most merciful. At the very beginning, all praises and gratitude belong to the Almighty Allah, whose belongings were always with me and have given me the opportunity to perform the research successfully.

I would first like to thank my supervisor, Dr. Asif-Uz-Zaman Khan, Associate Professor, Department of Urban and Regional Planning (DURP), Bangladesh University of Engineering and Technology (BUET), for his constant support, advice, and valuable suggestions, which were invaluable in the whole research work. I have learned a lot from him and consider myself a lucky one for getting the opportunity to work under his guidance.

I am grateful to Fajle Rabbi Ashik and Md. Hamidur Rahman for their contribution to this research work. Both of them helped me to formulate the concept of this research and prepare the database. I also thank Moshiur Rahman, Ahmed Aflan Prithul, and Ivee Baral for their assistance in the data collection process. I appreciate all of my colleagues in my department, especially Nawshin Tabassum, Sadia Afroj, Paromita Shome, and Md. Waliullah for their valuable support and encouragement.

Finally, I must express my profound gratitude to my parents, wife, family members, undergraduate and postgraduate classmates, teachers, colleagues, and friends for providing unwavering support and continuous encouragement throughout the process of researching and writing this thesis. This accomplishment would not have been possible without them. I pray to Allah for their every success and happiness. Thank you.

ABSTRACT

Pedestrian crashes have become a major safety concern in urban areas throughout the world, including Bangladesh. This scenario is no better in Dhaka, the capital and megacity of Bangladesh. From 1998 to 2014, more than 10 thousand crashes occurred here, and 4,514 pedestrians died in those crashes. To improve this critical situation, researchers have been trying to identify the contributory factors behind pedestrian crashes through studies at both macroscopic and microscopic levels. Macroscopic level pedestrian crash occurrences analysis and microscopic level pedestrian crash severity analysis are the most common techniques used for identifying contributory factors behind pedestrian crashes. Recent literature suggests to improve pedestrian safety by altering the built environment of urban areas considering its effect on pedestrian crashes. Therefore, identifying contributory built environment factors behind pedestrian crashes is important to reduce the number of crashes and their severity level.

In the case of macroscopic level pedestrian crash occurrences analysis, built environment-related factors have primarily been examined in the developed countries, resulting in a limited understanding of the phenomenon in the context of developing countries. Methodologically, these studies mostly used global regression models, which failed to incorporate spatial autocorrelation and spatial heterogeneity. Although a few of these studies used spatial regression models, they applied them randomly without following a comprehensive logical framework behind their selections. This study aimed to develop a comprehensive spatial regression modeling framework to examine the relationships between pedestrian crash occurrences and the built environment at the macroscopic level in Dhaka. Using secondary data, the study applied one global non-spatial model, two global spatial regression models, and two local spatial regression models following a comprehensive spatial regression modeling framework. The analysis results identified the factors that were found to significantly contribute to pedestrian crash occurrences in Dhaka. Those factors were employed person density, mixed and recreational land use density, primary road density, major intersection density, and share of non-motorized modes. Except for the last factor, all the other ones were positively related to pedestrian crash density.

Among the five models used in this study, the multiscale geographically weighted regression (MGWR) performed the best as it calibrated each local relationship with distant spatial scale parameter. The findings and recommendations presented in this study would be useful for reducing pedestrian crashes and choosing the appropriate model for crash analysis.

In the case of microscopic level pedestrian crash severity analysis, a large number of studies tried to explore the relationships between the built environment and pedestrian crash severity in developed countries. Unfortunately, there is a lack of similar studies in developing countries, especially Bangladesh. Methodologically, the contributory factors influencing pedestrian crash severity are commonly identified through global logistic regression (GLR) models. However, these models are unable to capture the spatial heterogeneity in the relationships between the dependent and independent variables. The local logistic regression model, such as geographically weighted logistic regression (GWLR), can potentially overcome this issue. Still, the application of local logistic regression to model pedestrian crash severity is absent in the literature. Therefore, this study applied the GWLR technique to explore spatially heterogeneous relationships between the natural and built environment-related factors with pedestrian crash severity in Dhaka. First, using secondary data, a binary logistic regression model was developed to identify significant factors influencing pedestrian crash severity. Results of the model showed that the probability of fatal pedestrian crash occurrence increased at night, in unlit locations, and during adverse weather conditions. Also, the likelihood of fatal crashes increased on straight and flat roads and at locations with more bus stops. On the other hand, the chance of fatal crashes reduced around institutional land uses and when medians exist on roads. Finally, this study explored spatial variation in the effect intensity of these significant variables across the study area using the GWLR technique. High-intensity variation across the study area was found for road geometry and institutional land use factors. On the other hand, low-intensity variation was found for light conditions and the presence of median factors. This technique can be applied in any area, and the results would be helpful to provide insights into the spatial dimension of traffic safety.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Pedestrian crashes have become a major safety concern in urban areas throughout the world, especially in developing counties. Around 1.35 million people die every year due to traffic crashes, and 22% of them are pedestrians. Significantly, more than 90% of those deaths happen in developing countries [1]. This situation is no better in Bangladesh. The Accident Research Institute (ARI) of BUET found that about 84 thousand traffic-related casualties occurred in Bangladesh from 1998 to 2014 [2]. Of these, 28 thousand were pedestrians. In addition, 13.3% of the pedestrian casualties occurred in Dhaka, the capital and megacity of Bangladesh.

To improve this grave situation, researchers around the world have conducted a large number of studies both at macroscopic and microscopic levels to identify the contributory factors behind pedestrian crashes by examining the relationship between crash occurrences and crash-inducing factors [3-5]. Understanding the contributory factors behind crashes is very important to take effective countermeasures to reduce crashes and their severity level, and subsequently, to improve pedestrian safety [6, 7]. Pedestrian crash occurrences (frequency/rate/density) analysis at a macroscopic level and pedestrian crash severity analysis at a microscopic level are the most common techniques used for identifying contributory factors behind pedestrian crashes [8].

In recent years, macroscopic level crash occurrences analysis has become popular among transportation planners for alleviating safety-related problems [9]. In such analysis, crash numbers are aggregated at a spatial unit (e.g., counties, block groups, wards, census tracts, traffic analysis zones) to examine its association with a number of crash-inducing contributory factors of the spatial unit [4, 5]. This type of analysis helps to identify safety problems in larger areas, explain spatial variation in crash frequency, and develop long-term safety improvement policies [8]. On the other hand, crash severity analysis uses the severity level of each crash (e.g., fatal, non-fatal) as the dependent variable and examines its relationship with all the potential crash-inducing contributory factors [6]. This analysis is also very helpful in identifying contributory factors at a more microscopic level than the previous one, and consequently, helps to reduce crashes and their severity level [6].

In the sustainable development age, urban planners advocate effective urban planning strategies (e.g., compact city development, TOD, smart growth) to re-design cities by altering their built environment [10-12]. These strategies help to develop sustainable cities by minimizing travel distance, reducing automobile uses, and increasing active mode use by increasing mixed, high density, and transit-oriented development within the cities [11, 13]. However, one of the sustainable development goals is to reduce the number of crashes and their severity level in the cities [1]. This goal is often neglected by urban and transportation planners [14]. This leads to dire consequences for the pedestrians, the most vulnerable segment of the road users [1]. Urban and transportation planners can improve pedestrian safety by altering the built environment of urban areas considering its relationships to pedestrian crash occurrences and their severity level [14].

Several studies have tried to explore the impact of the built environment on pedestrian crash occurrences [5, 7, 8, 14-19] and pedestrian crash severity [20-22] in the context of developed countries, e.g., western and European countries; whereas, there is a scarcity of literature in the context of developing countries, especially for the global south region. However, it is essential to explore contextual differences in crash factor identification as contributory crash factors could vary from one context to another [6]. Extremely high population density in urban areas, speedy growth of population, unplanned land use and transportation system, heterogeneous traffic movement, and poverty are among the major challenges in the cities of the developing countries, which make the built environment of these cities different from the developed countries' cities [23]. Without contextualization, knowledge regarding contributory crash factors would be limited and not be helpful to take proper countermeasures [24].

For modeling crash frequency and crash severity, most of the previous studies used non-spatial global regression models [6, 15, 16, 25-28]. However, non-spatial global regression models are unable to consider major characteristics of spatial data, including spatial dependency (spatial auto-correlation) and spatial non-stationarity (spatial heterogeneity) [29]. Crash occurrences are spatial phenomena having both spatial characteristics [3, 30, 31]. Local spatial regression models can acknowledge both spatial dependence and spatial non-stationarity [32, 33]. The application of global or local spatial regression models in crash-related studies is very rare. However, this approach could produce more reliable and accurate results [9, 34]. Therefore, to explore the relationship between built environment and pedestrian crash occurrences as well as pedestrian crash severity, it would be worthwhile to apply all the potential global and local regression models and find out the best one among them, which could produce more reliable and accurate results.

To address the existing contextual and methodological gaps in the existing literature, this study aimed to explore the effects of the built environment on the pedestrian crash occurrences and severity in Dhaka using spatial and non-spatial regression models and find out the model, which performs the best.

1.2 Objectives of the Study

The objectives of the study are as follows:

- To explore the effects of the built environment on pedestrian crash occurrences at a macroscopic level.
- To explore the effects of the built environment on pedestrian crash severity at a microscopic level.
- To compare the local and global as well as spatial and non-spatial regression models used to examine the relationship between the built environment and pedestrian crashes.

1.3 Organization of the Thesis

This thesis is organized into seven chapters. In **Chapter 1**, the background, aim, and objectives of the study are presented. A comprehensive literature review was conducted to summarize the findings from the previous studies and identify methodological challenges and gaps existing in the literature, which are outlined in **Chapter 2**. A detailed methodological framework and limitation of this study are described in **Chapter 3**. **Chapter 4** discusses the findings related to the examination of the effects of the built environment on pedestrian crash occurrences at a macroscopic level. In **Chapter 5**, the effects of the built environment on pedestrian crash severity are explored and discussed. In **Chapter 6**, case-specific analyses are presented to bridge between macroscopic and microscopic analysis. Major findings of the research and recommendations are summarized in **Chapter 7**.

CHAPTER 2: LITERATURE REVIEW

In this chapter, findings from the existing literature related to the effects of built environment factors on pedestrian crash occurrences and pedestrian crash severity are presented after conducting an extensive literature review. Then, the knowledge and methodological gaps existing in the literature are discussed. After that, existing pedestrian safety-related studies conducted in Bangladesh are summarized. The main contributions of this study are summarized at the end of this chapter.

2.1 Factors Influence Pedestrian Crash Occurrences and Severity

To determine how authorities can create a safer walking environment for the pedestrians by reducing pedestrian crashes, a large number of studies tried to explore the relationship between a variety of factors with pedestrian crash occurrences and crash severity outcome.

In macroscopic pedestrian crash occurrences analysis, first, the number of pedestrian crashes that occurred within a particular time period is aggregated at a spatial unit, mostly the lowest administrative unit: counties, block groups, wards, census tracts, traffic analysis zones [4, 5]. Then, spatial unit-wise crash frequency/ rate/ density is estimated and used as the dependent variable. Finally, models are developed to explore relationships between the dependent variable with a variety of independent variables of the spatial unit [35]. Since this type of analysis uses aggregate data of the spatial unit, it is not possible to incorporate individual crash-related factors, for example: pedestrian and driver characteristics (e.g., age, gender, experience), crash details (e.g., time of occurrences, locational attributes, weather condition). In general, two types of crash-inducing factors are considered in such studies: a) socio-economic factors and b) built environment factors.

To identify the effects of socio-economic factors on pedestrian crash occurrences, researchers considered a variety of factors: population density [14, 15], employment density [8, 16, 18], proportion of children/ senior citizen [16, 36], proportion of population from different race [7, 15], poverty level/ median income [16, 18], and so on. The effects of built environment factors on pedestrian crash occurrences are described in **Section 2.1.1**. As this study wanted to explore the relationships between pedestrian crash occurrences and the built environment, only two socio-economic factors were considered: population and employment density. These two variables are also considered as important variables to measure the built environment [37]. Therefore, they were incorporated into the study. Previous studies showed that the rest of the socio-economic factors had limited contribution to such studies, which was also a major reason for omitting these variables [17, 35].

In the case of microscopic level pedestrian crash severity analysis, the severity (e.g., fatal, non-fatal) of each individual crash is considered as dependent variable and models are developed to explore the relationship between crash severity outcomes with a variety of independent variables [6, 27, 38]. These independent variables can be divided into five broad categories: a) pedestrian characteristics, b) driver characteristics, c) vehicle characteristics, d) natural environment characteristics, and e) built environment characteristics. Pedestrian characteristics related factors include gender, age, alcohol intake condition, behavior, and clothing of the pedestrian [39-42]. Driver characteristics include gender, age, skill, alcohol intake condition, and experience of the drivers [40, 42, 43]. Vehicle characteristics include vehicle type, vehicle speed, and vehicle fitness [6, 42-44]. Details of the natural and built environment factors are presented in **Section 2.1.2**. Though the primary aim of the study was to focus on built environment factors, this study also incorporated natural environment factors along with built environment factors to make the study more comprehensive. The rest of the factors were not included due to having a large number of missing values in the data set, which is also discussed in detail in **Section 3.4.2**.

2.1.1 Influence of Built Environment on Pedestrian Crash Occurrences

Several studies tried to explore the impact of the built environment on pedestrian crash occurrences in the context of developed countries, for example, western and European countries [5, 7, 8, 14-19]. These studies mostly considered three characteristics of the built environment to explore the relationship with pedestrian crash occurrences: a) density, b) land use, and c) roadway and traffic.

Among the density variables, population and employment density were found to be significant in the previous studies. Areas having high population density were associated with higher pedestrian crashes [16, 18]. However, conflicting findings were found in the case of employment density. A large number of studies showed a positive association between pedestrian crash frequency and employment density [8, 16, 18]. In contrast, an opposite association was also found in the study of Chen and Zhou [14].

Conflicting findings were found from the existing literature regarding the relationship between pedestrian crash occurrences and land use. The proportion of commercial land use had a positive association with pedestrian crash occurrences [7, 8, 17, 19]. However, inconsistent findings were found regarding industrial and residential land use. Several studies found that residential and industrial land use proportions were negatively associated with pedestrian crash frequency [8, 14, 15]. Conversely, a positive association was also found in quite a few studies [7, 16-18]. For recreational (e.g., open space/ park) and mixed land use, prior studies showed both positive [15, 17, 45, 46] and negative [7, 8, 19] associations with pedestrian crash occurrences.

In the case of roadway and traffic characteristics related variables, the density of different road classes and intersections had a significant association with pedestrian crash occurrences. A higher proportion of local roads were correlated with fewer pedestrian crashes [8, 18]. However, this relationship was found opposite for collector and arterial roads [8, 16, 19]. Three-legged intersection density was negatively associated with pedestrian crash occurrences [15]. On the other hand, the density of more complicated intersections (e.g., four-legged intersection, five-legged intersection) was positively associated with pedestrian crashes [14, 15, 18]. Sidewalk density was negatively related to pedestrian crash occurrences [14, 18]. On the other hand, areas with higher transit station/ bus stop density were likely to have more pedestrian crashes [7, 8, 15]. Prior studies also showed that the modal share of walking [14] and households without vehicles [18, 47] were positively associated with the frequency of pedestrian crashes. A summary of the significant factors affecting pedestrian crash occurrences is presented in **Figure 2-1**.

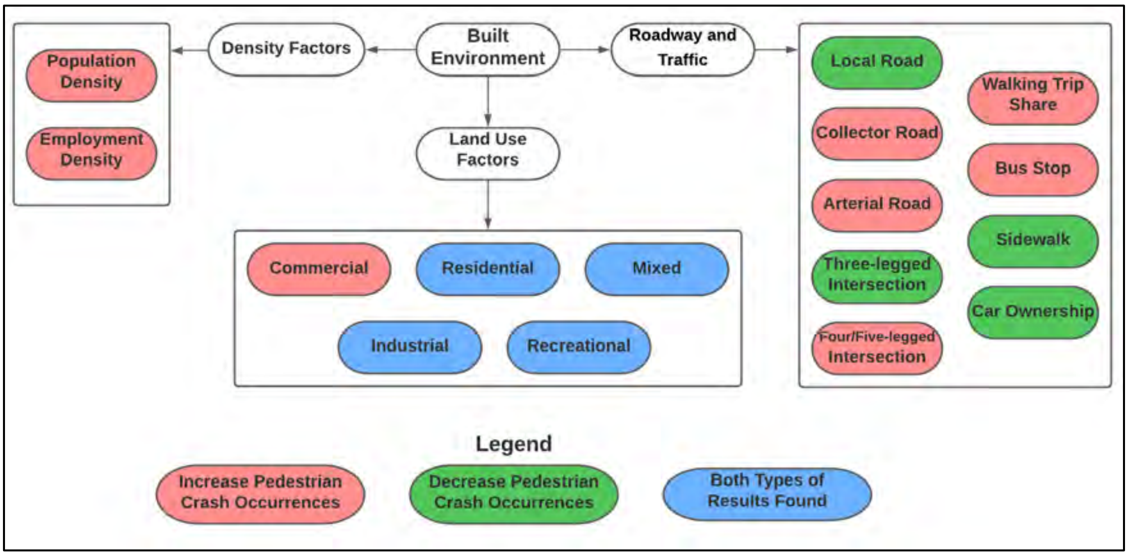

Figure 2-1: Factors influencing pedestrian crash occurrences

2.1.2 Influence of Built Environment on Pedestrian Crash Severity

A large number of studies have tried to identify contributory factors influencing pedestrian crash severity mostly in the context of developed countries; also, a few of the studies are from developing countries [e.g., 6, 20-22, 28, 41, 44, 48, 49, 50]. Previous studies showed that built environment characteristics had a significant relationship with the pedestrian crash severity. Those contributory built environment factors can be categorized broadly into three categories: (1) roadway characteristics, (2) land use characteristics, and (3) presence of key features. In addition, previous studies also found the natural environment factors (e.g., time of day, day of the week, season, weather condition, light condition) influential. Details of these factors and their relationships with pedestrian crash severity are presented in **Table 2-1**.

Table 2-1: Findings from previous studies on contributory natural and built environment factors influencing pedestrian crash severity

Factors	**Major findings**
Natural environment characteristics	
Time of day	Previous studies reported that pedestrian crashes that occurred at night tended to be more severe than those that happened during the day [40, 50, 51].
Day of week	The likelihood of fatal crashes increased during weekends compared to weekdays [50, 52].

Factors	Major findings
Season of year	Previous studies showed contradicting results regarding the effect of season on pedestrian crash severity. For example, the chance of fatal pedestrian crashes increased during the summer season, as per Pour-Rouholamin and Zhou [40]. However, Mohamed, Saunier, Miranda-Moreno and Ukkusuri [53] reported that severity tended to increase during the winter and fall.
Light condition	Uniform results were reported regarding lighting conditions in the literature. The probability of fatal pedestrian crash occurrence increased at dark and unlit locations as well as places where street lights were not present [40, 41, 49, 50, 54].
Weather condition	Most studies found that adverse weather (e.g., foggy, rainy) increased pedestrian crash severity compared to fair weather [6, 41, 50, 55, 56]. However, Kim, Ulfarsson, Shankar and Kim [43] reported the opposite result.
Built environment characteristics	
Roadway characteristics	
Location	Previous studies showed that pedestrian crashes that occurred at intersections tended to be less severe than crashes that occurred at non-intersection locations [44, 48, 57, 58].
Traffic control	Consistent results were reported in the literature about the relation between traffic control and pedestrian crash severity. Severity outcomes tended to be milder if crashes occurred at locations where traffic signals or signs or any control system were available compared to the places where any control system was absent [20, 40, 49, 56, 59].
Presence of median	Zafri, Prithul, Baral and Rahman [6] found that a median on the roadway reduced the probability of fatal pedestrian crash occurrence. In contrast, opposite results were also reported in the previous studies [20, 40].
Road geometry	Previous studies found that the likelihood of fatal crashes increased if the crash occurred on a curved and inclined road compared to straight and flat roads [50]. However, Zafri, Prithul, Baral and Rahman [6] reported the opposite result.
Road surface	The likelihood of fatal crashes increased if the collision occurred on untarred roads compared to tarred roads [50].

Factors	Major findings
Road class	If the pedestrian crash occurred on the road having a higher speed limit or more lanes, the crash outcome was likely to be more severe [40, 54]. Some studies also reported that pedestrian crashes on major roads tended to be more severe than local roads [43, 48].
Land use characteristics	
Residential land use	The probability of a fatal pedestrian crash tended to be lower if the crash occurred in a residential area [21].
Commercial land use	Pedestrian crashes in a commercial area tended to be more severe [43, 48].
Industrial land use	The likelihood of fatal crashes decreased in an industrial area [44].
Presence of key features	
Bus stop density	The chances of fatal and severe pedestrian injuries decreased with increasing bus stop density [20, 49, 60].
Presence of school	There is no consensus regarding whether the pedestrian crash that occurred near a school tended to be more severe or not. Some studies found that the presence of schools near crash locations decreased the chance of fatal crashes [20, 48], whereas Clifton, Burnier and Akar [49] reported the opposite result.

From the findings presented in the **Table 2-1**, it is clear that though several factors had a similar effect on pedestrian crash severity in all the studied areas, a large number of factors also had contradictory effects (e.g., the season of the year, weather condition, presence of median, road geometry, and presence of school) due to the contextual differences. So, it is necessary to explore the effects of the natural and built environment on pedestrian crash severity in the context of Dhaka to reduce crashes and their severity in the city.

2.2 Methodological Challenges

2.2.1 Pedestrian Crash Occurrences Analysis

To identify the contributory factors behind pedestrian crash occurrences at a macroscopic level, most of the previous studies used non-spatial global regression models, including ordinary least squares (OLS) [16], Poisson, and negative binomial regression models [15, 25, 26]. Global models are powerful statistical modeling tools that help to develop an overall model for the whole study area based on all observations of the area considering consistent (homogeneous) relationships between the dependent variable and independent variables over geographical space (spatial stationarity) [31]. Besides, non-spatial models are developed considering that all the observations are independent from each other [61]. Therefore, global non-spatial regression models are unable to consider major characteristics of spatial data, including spatial autocorrelation (spatial dependency) and spatial heterogeneity (spatial non-stationarity) [62]. Furthermore, spatial heterogeneity in relationships could be present if spatial dependence is found in the spatial data [31].

Crash occurrences are spatial phenomena that are usually found to be spatially correlated (spatial autocorrelation) and heterogeneous like all other spatial phenomena [3, 34]. Therefore, parameters estimated through global models for the whole study area may not truly represent local relationships in a large portion of the area as they fail to consider the spatial heterogeneity nature of the relationships [4]. In addition, estimated coefficients through non-spatial global models could be biased if spatial autocorrelation is present in the model [63]. Hence, non-spatial global models often produce unreliable results [64].

To address the limitations of non-spatial global regression models, researchers from various disciplines (e.g., ecology, sociology, epidemiology, public health, transportation, and geography) used global and local spatial regression models [31, 65]. Two of the widely used global spatial regression models are the spatial lag model (SLM) and spatial error model (SEM) [66, 67]. Few studies also used SLM and SEM to model crash occurrences for addressing spatial autocorrelation [63, 68]. Though these two models help develop more accurate results than non-spatial global regression models [63], they cannot address the spatial non-stationarity characteristics [31].

Local regression models acknowledge spatial heterogeneity and estimate localized version of parameters for each relationship between the dependent variable and independent variables across the study area, considering that their relationship may vary over space [69]. These models generate a separate model for each location of the study area considering spatial relationships with its neighbors [34]. Geographically weighted regression (GWR) is the most popular and widely used local regression technique [70]. However, very few traffic safety-related studies are available, which used different types of GWR for modeling crash occurrences: GWR for crash rate modeling [34], geographically weighted Poisson regression (GWPR) [3, 9], and geographically weighted negative binomial regression (GWNBR) [4] for crash frequency modeling. These studies' results showed that GWR (and other forms of GWR) performed better than the non-spatial global models [9, 34].

Spatial scale is the most fundamental concept of geographic information science. Various spatial processes could operate at different spatial scales [71]. In a macroscopic crash modeling study, the GWR model explored local relationships between the dependent variable and independent variables considering a constant spatial scale (global bandwidth) [34]. However, local relationships between the dependent and independent variables could operate at different spatial scales (local bandwidth for each relationship) [69]. For this reason, the estimation through the GWR could be inaccurate and biased [62]. Multiscale geographically weighted regression (MGWR) is the latest, extended, advanced, and flexible version of GWR, which develops the model by allowing spatial relationships between dependent and independent variables to operate at different spatial scales. Many studies in other disciplines show that MGWR produces more accurate results than GWR [65, 69, 71]. However, to the best of our knowledge, the application of MGWR for modeling crash occurrences at the macroscopic level is totally absent in the literature though it can potentially produce better results.

Apart from this aspect, all the available studies on macroscopic crash modeling using global and local spatial models are fragmented and unconnected. They just showed the application of only one local spatial model or only global spatial regression models and compared the results with the non-spatial global model. These studies applied spatial regression models randomly without following a comprehensive logical framework behind their model selections. However, no spatial model can effectively address both the spatial data characteristics (spatial autocorrelation and spatial heterogeneity) [61]. In other words, the appropriateness of applying a spatial model depends on the spatial data characteristics [62]. Comber, Brunsdon, Charlton, Dong, Harris, Lu, Lü, Murakami, Nakaya and Wang [62] pointed out that the application of the GWR model in a large number of studies has yielded some problems, which raise the question of whether the researchers selected the appropriate modeling technique and adequately comprehended the model's input, output, and assumptions. These problems make the application of the GWR model inappropriate and incomplete. Therefore, a study is required to develop a comprehensive framework of spatial regression modeling and compare non-spatial and spatial regression models to determine which spatial model should be appropriate for modeling crash occurrences at a macroscopic level in a given situation. However, there is no comprehensive study available in the literature.

2.2.2 Pedestrian Crash Severity Analysis

For crash severity analysis, most of the previous studies used global logistic regression (GLR) models: binary logistic regression [6, 54, 72, 73], multinomial logistic regression [27, 28, 50, 59, 74], ordered logit or probit model [48, 53, 75-77], ordered response model [40, 78], and generalized ordered probit model [49]. The GLR models are powerful statistical modeling tools that help to develop an overall model for the whole study area based on all observations of the area. Like the above-mentioned global regression model, they also consider a consistent relationship between the dependent and independent variables over the space (spatial stationarity/ spatial homogeneity) [31, 79]. Therefore, these models cannot capture the spatial variation (spatial non-stationarity/ spatial heterogeneity) in the relationships between the dependent and independent variables [80]. However, the relationships between crash severity and crash-inducing factors could vary significantly over the geographical space.

The local logistic regression model can capture spatial heterogeneity in the relationships between crash severity and crash-inducing factors by allowing the coefficient of each independent variable to vary over the geographical space [79, 81]. Geographically weighted logistic regression (GWLR) is a popular and effective local logistic regression modeling technique that has been successfully used in different fields, such as epidemiology [80, 82], transportation [83], geology [84], and hazards

[79]. However, to the best of the author's knowledge, the application of the local regression model in the crash severity-related study is absent in the literature. Therefore, to explore the relationships between the natural and built environment-related factors with pedestrian crash severity, it would be worthwhile to apply the GWLR method, which could produce more reliable and accurate results than GLR models by exploring spatially varying relationships.

2.3 Pedestrian Safety Research in Bangladesh

There were negligible numbers of studies available on pedestrian safety in Bangladesh until a few years back. However, pedestrian safety-related research has been growing in the recent years. Those studies can be classified into four broad categories: i) pedestrian crash pattern analysis, ii) exploring risky pedestrian behavior, iii) site (hotspot) specific pedestrian safety analysis, and iv) pedestrian crash severity. Nevertheless, no study was found that focused on the macroscopic level crash occurrences analysis in the context of Bangladesh.

In pedestrian crash pattern analysis, simple descriptive analysis is conducted to explore pedestrian crash patterns [85-89]. In pedestrian risky behavior analysis, researchers tried to explore the pedestrian's risky walking and road crossing behaviors [90-98]. In site (hotspot) specific pedestrian safety analysis, several roads/ intersections/ areas are selected to investigate pedestrian safety-related problems and recommend solutions [99-101]. In addition, a study was also found that identified pedestrian crash hotspots in Dhaka [88].

In pedestrian crash severity analysis, researchers identified factors influencing crash outcome (whether the crash outcome would be fatal or non-fatal) in Dhaka [6, 102, 103] and the highways of Bangladesh [104]. Those studies did not consider comprehensive built environment factors, especially land use and the presence of a key feature (hospital, school, bus stop), which remains a gap in the literature. In addition, all these studies used global regression model, for example, binary logistic regression [6, 104], latent segmentation-based ordered logit [102], multinomial logit [103], ordered logit [103], and partial proportional odds model

[103]. This also showed the importance of exploring spatial variation in the relationship between built environment factors with pedestrian crash severity.

2.4 Gaps and Contribution of the Study

This study attempted to fill two gaps in the literature:

a) **Contextual gap:** Relationship between built environment with pedestrian crash occurrences and pedestrian crash severity has primarily been examined in developed countries, resulting in a limited understanding in the context of developing countries, including Bangladesh. To address the contextual gap in the literature, this study aimed to explore the relationship between the built environment with pedestrian crash occurrences and pedestrian crash severity in the context of a developing country's city: Dhaka, the megacity and capital of Bangladesh. By far the largest city in the country, Dhaka has unique built environment characteristics and travel behavior patterns [23, 105]. As one of the most crash-prone cities in the world, it is a good case for conducting this study and would be a significant contribution to literature.

b) **Methodological gaps:** Another contribution would be addressing the methodological gaps: i) absence of application of advanced MGWR model and lack of comprehensive spatial regression modeling framework in the macroscopic crash study and ii) absence of exploring the spatially heterogeneous relationship between crash severity and the built environment at a microscopic level. Therefore, this study aimed to propose a comprehensive spatial regression modeling framework incorporating the MGWR model. The framework incorporated spatial autocorrelation and spatial heterogeneity as well as considered the spatial scale of spatial processes. This framework was aimed to apply in this study to model macroscopic pedestrian crash occurrences to find the appropriate modeling technique, which could produce more reliable and accurate results. In the case of pedestrian crash severity analysis, this study would contribute by exploring the spatially heterogeneous relationship between pedestrian crash severity and the natural and built environment by applying the local logistic regression technique. The findings of this study would be helpful for transportation and urban planners to identify appropriate modeling techniques, better understand the relationship between pedestrian crash occurrences and the built environment, as well as take proper countermeasures to reduce crashes and ensure a safe city for pedestrians.

CHAPTER 3: METHODOLOGY

In this chapter, the study area for this study is designated first. Then, data sources, data collection procedures, and database preparation for analysis are presented in separate sections. Finally, the data analysis procedure, including model specification and development, is described in detail.

3.1 Study Area

In this study, Dhaka City Corporation (DCC) area was taken as the study area. This area consists of two city corporations - Dhaka South City Corporation (DSCC) and Dhaka North City Corporation (DNCC). These two administrative areas are divided into 92 wards, the lowest unit of administrative area in Dhaka [106]. In addition, in the Revised Strategic Transport Plan (RSTP), the DCC area was divided into 92 Traffic Analysis Zones (TAZ) coinciding with the administrative boundary of the wards. The average size of each ward/ TAZ is around 150 hectares. Ward/ TAZ was used as the spatial analysis unit because these smallest administrative units have the comprehensive demographic data in the census. **Figure 3-1** shows the map of the study area. Map with ward number is presented in the Appendix (**Figure A1).** The missing part in the upper-middle portion of the study area is Dhaka Cantonment, which is not included within the DCC area (**Figure 3-1**).

Dhaka is one of the most densely populated megacities in the world with a population density of 45,000 inhabitants per square kilometer area [23, 107]. This city is also by far the largest city in the country and the commercial and administrative hub of the country. On a regular working day, around 21 million trips are generated within the study area [105]. Among the trips, around 20% of the trips are walking trips (**Figure 3-2**). Huge traffic congestion, poor public transport service, lack of coordination among the transportation stakeholders, absence of adequate pedestrian facilities, insufficient parking facilities, operation of motorized and non-motorized modes on the same roads, an increasing number of private vehicles (e.g., car, motorcycle), the mismatch between land use and transportation infrastructure, and a large number of road crashes are some of the major transportation-related problems within the study area [107].

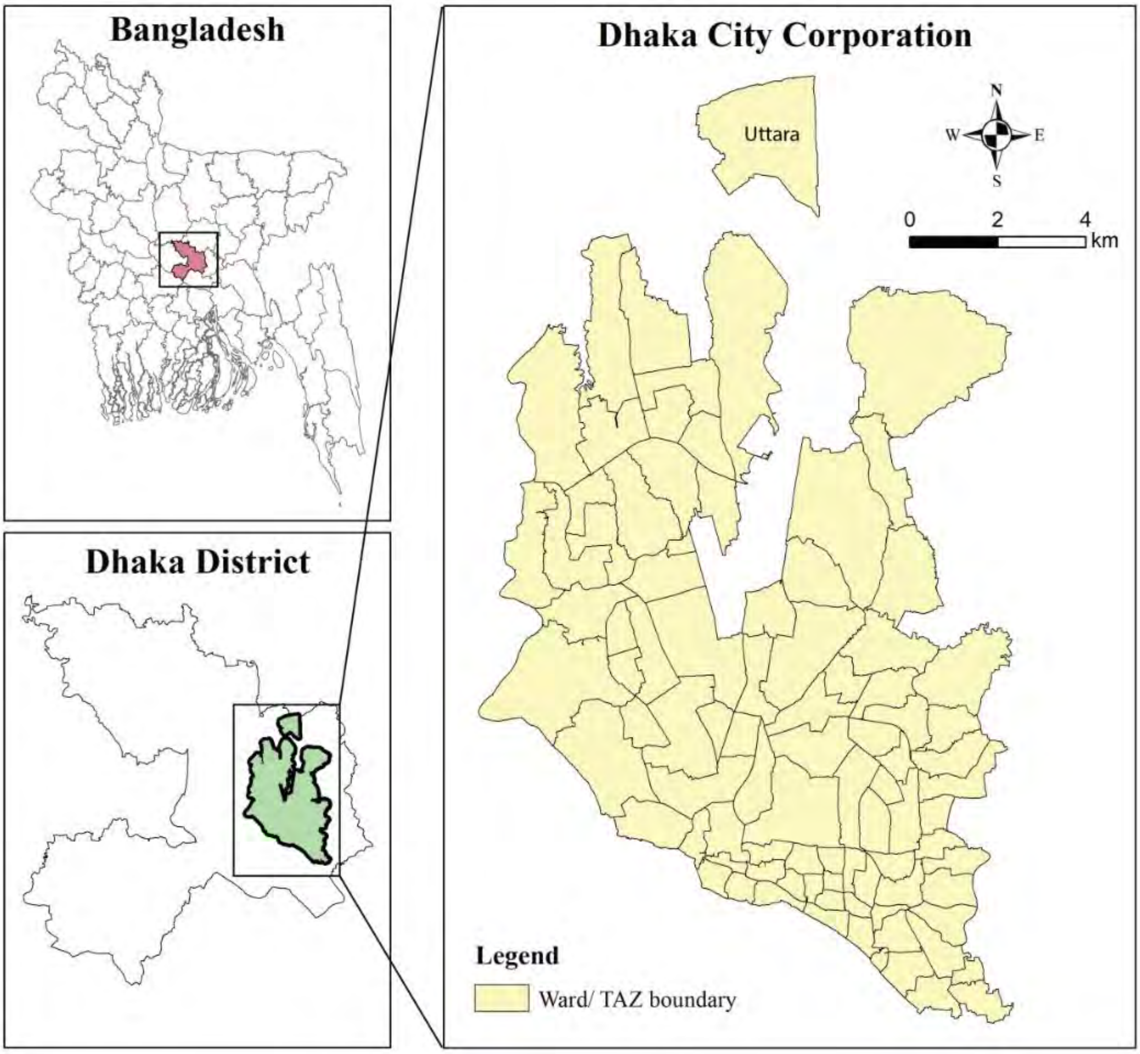

Figure 3-1: Map of the study area: Dhaka City Corporation

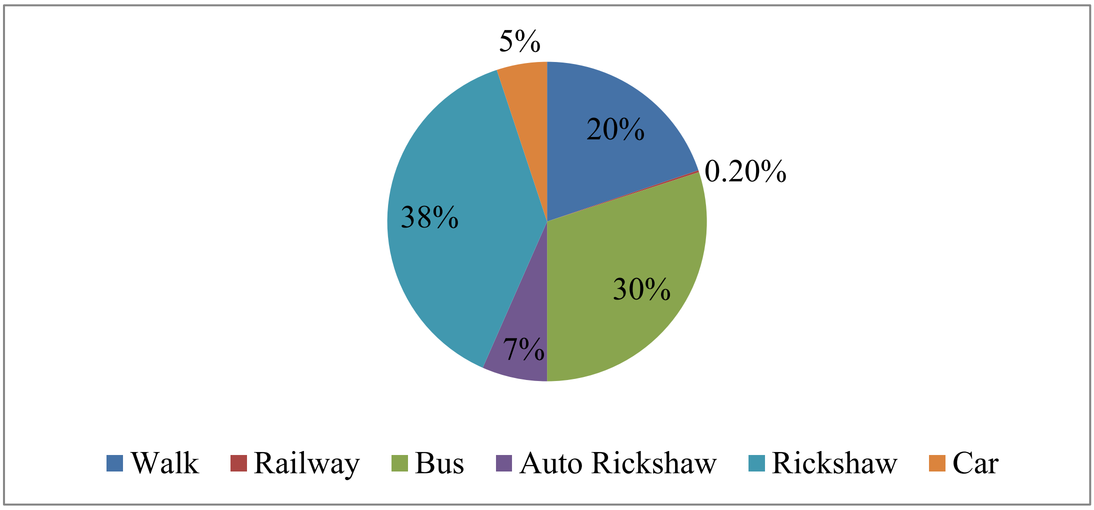

Figure 3-2: Modal share in Dhaka

From 1998 to 2014, more than 10 thousand crashes occurred here, and 4,514 pedestrians have died in those crashes [2]. **Figure 3-3** shows that the number of crashes in Dhaka fluctuated between 300-450 per year and more than 300 people died yearly in those crashes. In addition, more than 55% of those crashes involved pedestrians. Among the deaths related to crashes, around 70% were pedestrians.

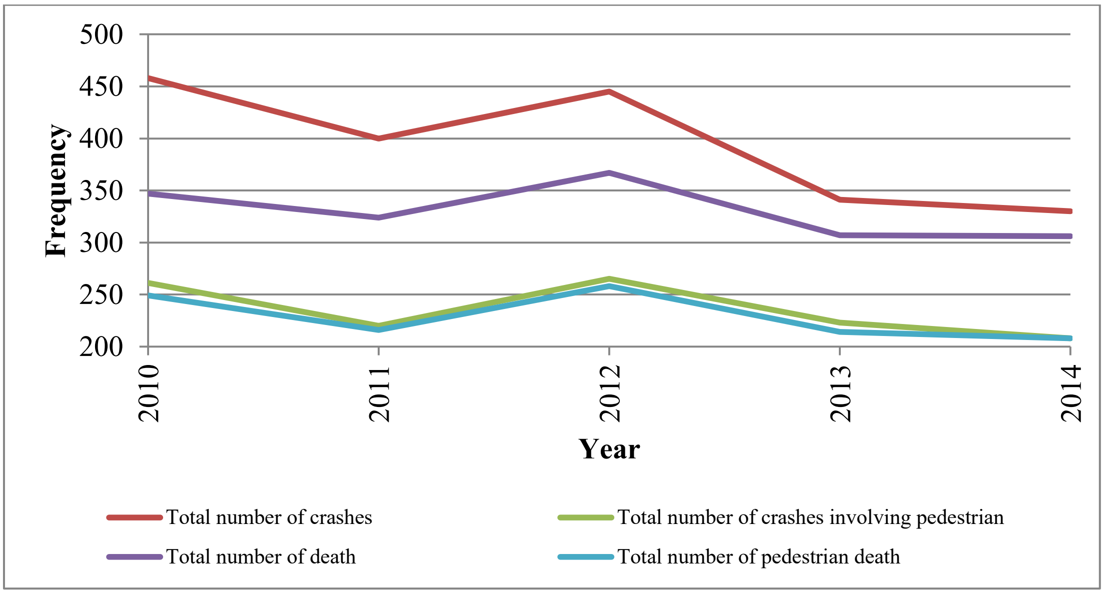

Figure 3-3: Number of crashes and deaths in Dhaka from 2010-2014

3.2 Data Collection and Processing

3.2.1 Pedestrian Crash Occurrences Analysis

To analyze pedestrian crash occurrences, a GIS-based database for the study area was prepared, incorporating pedestrian crash occurrence and built environment characteristics-related data. Pedestrian crash data along with their location were collected from the Accident Research Institute (ARI) of Bangladesh University of Engineering and Technology (BUET). According to the database, a total of 1,309 pedestrian crashes occurred between 2010 and 2015 in the study area. Using the location of the crash data, the number of pedestrian crashes that occurred in each ward was determined. Then, pedestrian crash density was calculated by dividing the pedestrian crash frequency by the area of the corresponding ward. This study used pedestrian crash density as the dependent variable.

To cover maximum dimensions of the built environment, this study categorized independent variables under three broad headings: density characteristics, land use characteristics, and roadway and traffic characteristics. Density characteristics were represented by ward-wise population density, job density, and employed person density. Density data were obtained from ‘Population and Housing Census: Community Series, Zila: Dhaka, 2011’ and ‘Economic Census 2013’ documents, which were prepared by the Bangladesh Bureau of Statistics (BBS). The density of six land use types was calculated for each ward: residential, commercial, industrial, mixed, recreational, and institutional. Land use data were collected from the Detailed Area Plan (DAP) (2015) of Dhaka, which was prepared by the Capital Development Authority (RAJUK).

Roadway and traffic characteristics included ward-wise local road density, collector road density, arterial road density, minor intersection density, major intersection density, and link-node ratio. Traffic characteristics included non-motorized modes trip share, public transport share, private modes share, and paratransit modes share. Physical road network data were obtained from RAJUK (2016) and they were cross-checked using Open Street Maps (OSM) 2019. The density of different road classes, intersection density, and link-node ratio were calculated using the collected database. Traffic characteristics-related data were collected from RSTP, which was prepared by DTCA. All the above-mentioned collected data were attached with their corresponding ward in the GIS-based database. **Table 3-1** briefly describes all the independent and dependent variables for pedestrian crash occurrences analysis. A detail description of the dependent and independent variables is presented below.

Dependent Variable:

- *Pedestrian crash density:* Here, the dependent variable was ward-wise pedestrian crash density. In ArcGIS, all the pedestrian crash data were first plotted according to their latitude and longitude. Then, the number of crashes in each ward was estimated through the spatial join tool. Then, pedestrian crash density was derived by dividing the crash frequency by the area of the corresponding ward (hectare).

Independent Variables:

<u>Density characteristics related factors</u>

- *Population density:* This variable was calculated by dividing the number of people living in a ward by the corresponding ward's area (hectare).
- *Job density:* Job density at the ward level was calculated as the number of jobs available in a ward divided by the total area of the ward (hectare).
- *Employed person density:* This variable at the ward level was calculated as the ratio of the number of employed persons living in a ward and the total area of the ward (hectare).

<u>Land use characteristics related factors</u>

- *Residential, commercial, industrial, recreational land use density:* RAJUK marked residential, commercial, industrial, and open space areas in the DAP (2015). From the DAP, areas of residential use, commercial use, industrial use, and open space in each ward were estimated in hectares. Then, densities of residential, commercial, industrial, and recreational uses were estimated by dividing the residential, commercial, industrial, and open space area (hectare) by the total area of the corresponding ward (hectare), respectively.
- *Mixed land use density:* RAJUK also delineated mixed use areas in the DAP (2015). Three types of mixed land use were found in DAP (2015): a mixture of commercial and industrial, a mixture of commercial and residential, and a mixture of commercial, industrial and residential. This study dissolved these three categories into a single category and named it mixed land use. The area of mixed land use in each ward was estimated in hectares from the DAP. Then, the density was estimated by dividing the mixed use area (hectare) by the total area of the corresponding ward (hectare).
- *Institutional land use density:* RAJUK marked administrative and institutional land use areas in the DAP (2015). This study dissolved these two categories into a single category and named it institutional land use. From the

DAP, the area of institutional land use in each ward was estimated in hectares. Then, the density was estimated by dividing the institutional use area (hectare) by the total area of the corresponding wards (hectare).

Roadway and traffic characteristics related factors

- *Local, secondary, and primary road density:* In Dhaka, a clear road hierarchy was absent. Therefore, in this study, local roads were defined as roads having one or two-lane, secondary roads were defined as roads having four-lane, and primary roads were defined as roads having six-lane or more. The local, secondary, and primary road densities were calculated by dividing the length of local, secondary, and primary road in a ward (meter) by the total area of the corresponding ward (hectare), respectively

- *Minor and major intersection density:* In RSTP, DTCA mentioned major and minor roads of Dhaka based on traffic volume. If all the legs of an intersection were part of the major road network of Dhaka, this intersection was considered as major intersection in this study. Otherwise, the intersection was termed as minor intersection. Numbers of minor and major intersections presented in each ward were calculated first. Then, densities of minor and major intersection at the ward level was calculated by dividing the number of minor and major intersections in a ward by the total area of the corresponding wards (hectare), respectively.

- *Link-node ratio:* The link-node ratio is a measure of connectivity. This variable at the ward level was calculated as the ratio of the number of links in a ward and the number of nodes in the corresponding ward. A node is an intersection of the transportation network. In comparison, a link is a roadway between two intersections. A higher value of this variable means better connectivity.

- *Modal share of non-motorized, public, private, and paratransit modes:* This variable presents the percentage of total trips in a ward was made by non-motorized (e. g., walking, cycling, rickshaw), public (e. g., bus, train), private (e.g., car, microbus, motorcycle), and paratransit (e. g., CNG, leguna) modes.

Table 3-1: Variable description for pedestrian crash occurrences analysis

Variable name	Variable description/ Unit	Data Source
Dependent variable		
Pedestrian crash density	Pedestrian crash frequency/ total area [ha]	ARI, BUET
Independent variable		
Density characteristics related factors		
Population density	Number of people/ total area [ha]	BBS
Job density	Number of jobs available/ total area [ha]	
Employed person density	Number of employed persons live in/ total area [ha]	
Land use characteristics related factors		
Residential land use density	Residential area [ha]/ total area [ha]	RAJUK
Commercial land use density	Commercial area [ha]/ total area [ha]	
Industrial land use density	Industrial area [ha]/ total area [ha]	
Mixed land use density	Mixed used area [ha]/ total area [ha]	
Recreational land use density	Recreational area [ha]/ total area [ha]	
Institutional land use density	Institutional area [ha]/ total area [ha]	
Roadway and traffic characteristics related factors		
Local road density	One-or two-lane road length [m]/ total area [ha]	OSM, RAJUK
Secondary road density	Four-lane road length [m]/ total area [ha]	
Primary road density	Six-lane or more road length [m]/ total area [ha]	
Minor intersection density	Number of minor intersections/ total area [ha]	
Major intersection density	Number of major intersections/ total area [ha]	
Link-node ratio	Number of nodes/ number of links	
Non-motorized modes share	Percentage of the total trip by non-motorized modes	DTCA
Public mode share	Percentage of the total trip by public transport mode	
Private modes share	Percentage of the total trip by private transport modes	
Paratransit modes share	Percentage of the total trip by paratransit modes	

3.2.2 Pedestrian Crash Severity Analysis

From the collected 1,309 pedestrian crash data (**Section 3.2.1**), around 1,166 crash data were found usable after data cleaning for pedestrian crash severity analysis. These collected crash data also included crash severity level, address and geolocation of crash location, roadway characteristics at the crash location, time of crash occurrence, and weather condition at the time of the crash.

Three dimensions of the built environment were covered in this analysis: 1) roadway characteristics, 2) land use characteristics, and 3) presence of key features. Land use data were collected from Detailed Area Plan (DAP) (2015) in shapefile format, which was prepared by RAJUK. This study considered three key features: educational institute, hospital, and bus stop. Data of educational institutes and hospitals were collected from the DAP. Bus stop data were obtained from 'Dhaka Bus Network and Regulatory Reform Implementation Study and Design Work 2012', which was prepared by DTCA.

Previous studies showed that the built environment's impact could be better captured if built environment characteristics surrounding 250m of each crash location are considered [102, 108]. Therefore, the proportion of different types of land uses, and presence of educational institutes, hospitals, and the number of bus stops within 250m from each crash location were estimated from the shapefile and joined with the corresponding crashes based on the crash location. In this way, a geodatabase was prepared in shapefile format. Descriptions of the collected data (independent variable) are presented in **Table 3-2**.

Table 3-2: Independent variables for pedestrian crash severity analysis

Main dimension	Sub dimension	Factor	Levels	Data Source
Natural environment characteristics		Season	Summer, rainy season, winter	ARI, BUET
		Time of day	Day, night	
		Light condition	Well-lit, Unlit	
		Weather condition	Good, adverse (e.g., rainy, foggy)	
Built environment characteristics	Roadway characteristics at the crash location	Location	Non-intersection, intersection	
		Traffic control	Uncontrolled, controlled	
		Presence of median	No, yes	
		Road geometry	Straight and flat, others (e.g., curve, slope)	
		Road surface	Brick, sealed	
		Road class	Highway, others (e.g., city road, feeder road)	
	Land use proportion within 250 m buffer from crash incidence location	Residential		RAJUK
		Commercial		
		Industrial		
		Mixed		
		Institutional		
		Restricted		
		Open space		
	Presence of key features within 250 m buffer from crash incidence location	Presence of educational institute	No, yes	
		Presence of hospital	No, yes	
		Number of bus stop		DTCA

3.3 Data Analysis and Model Estimation

3.3.1 Modeling Pedestrian Crash Occurrences

This study proposed a spatial modeling framework to explore the effects of the built environment on pedestrian crash density incorporating spatial autocorrelation and spatial heterogeneity. It is presented in **Figure 3-4**. This framework was developed with the help of previous literature [e.g., 61, 62, 69, 109].

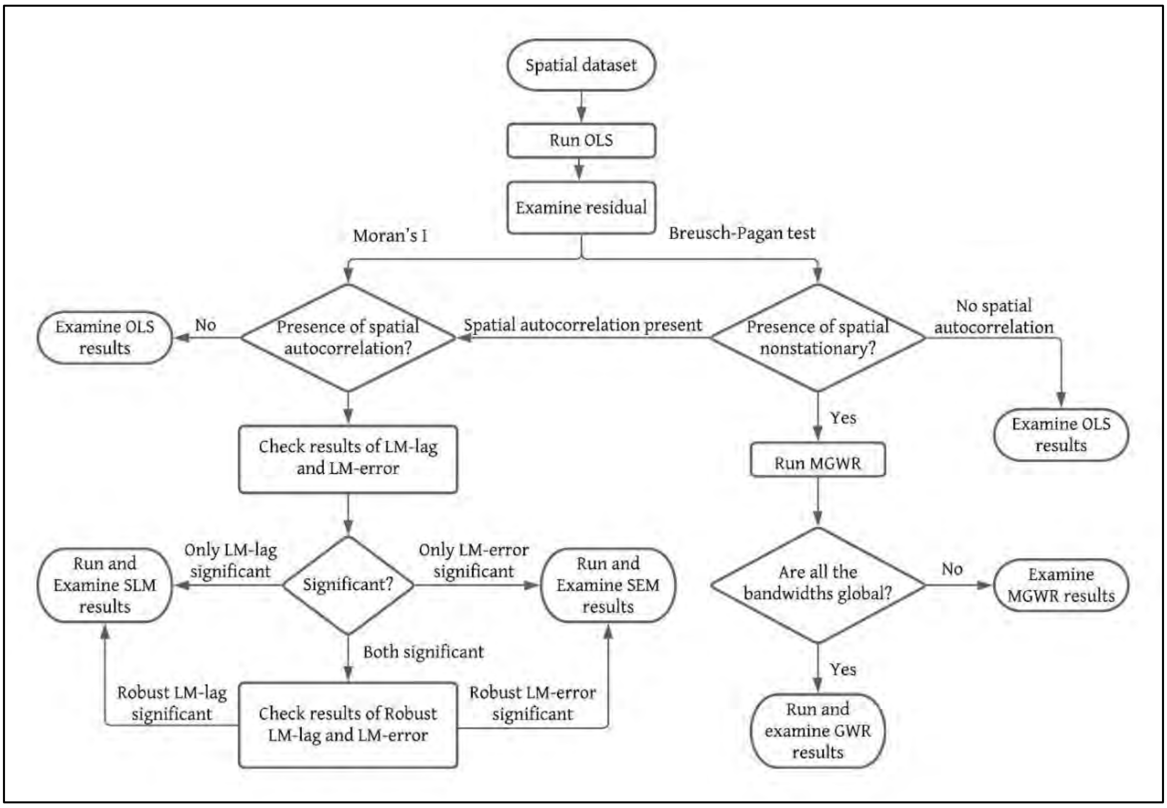

Figure 3-4: Spatial regression modeling framework for pedestrian crash occurrence modeling

3.3.1.1 Specification and estimation of ordinary least squares (OLS) model

For all spatial regression analyses, the OLS model is the appropriate starting point [61, 110]. The OLS is a global non-spatial modeling technique that helps to model the linear relationships between a continuous dependent variable and a set of independent variables assuming constant and stationary relationships over the geographical space. The OLS form in this study is characterized by:

$$y_i = \beta_{\circ} + X_i\beta + \varepsilon_i \ , \quad i = 1,\ldots\ldots, n$$

Here, y_i is the pedestrian crash density in Ward i, intercept is expressed by $\beta_{\circ}$, X_i is the matrix of built environment-related independent variables, random error is expressed by ε_i, and β is the matrix of regression coefficients.

In the first step of this study, an OLS model was developed. Before developing the model, Pearson's correlation coefficients were estimated to explore the correlation among the independent variables. Strongly correlated variables ($r > 0.6$) were not considered for developing the model to eliminate multicollinearity in the OLS model. Outliers of the dataset were also treated. Using the rest of the independent variables, this study calibrated an OLS model through a stepwise forward procedure. The presence of multicollinearity within the model was assessed through condition number (*CN*) and Variance Inflation Factor (*VIF*). The OLS model was estimated through the GeoDa software. Uttara Ward (**Figure 3-1)** was not included in the model development process because this ward is disconnected from the other wards, which could affect the estimation of the spatial models.

3.3.1.2 Checking the presence of spatial autocorrelation in OLS model

As the OLS model is a global non-spatial model, this model is not appropriate if the residuals of the model are spatially correlated (spatial autocorrelation) [34]. After developing the OLS model, Moran's I tool was used to assess the presence of spatial autocorrelation in the residuals. A significant Moran's I value indicates the presence of spatial autocorrelation, which emphasizes the need to develop global spatial regression models such as SLM and SEM [62, 63].

3.3.1.3 Specification and estimation of the spatial lag model (SLM) and spatial error model (SEM)

The SLM can incorporate spatial autocorrelation between the dependent and independent variables by integrating a "spatially-lagged dependent variable" in the model [65, 109]. SLM is denoted as:

$$y_i = \beta_{\circ} + X_i\beta + \rho W_i y_i + \varepsilon_i \ , \quad i = 1,\ldots\ldots, n$$

Where, y_i = pedestrian crash density in Ward i; $\beta_\circ$ = intercept; X_i = matrix of built environment-related independent variables in Ward i; ρ = spatial autoregressive parameter (*Rho*), and W_i = spatial weights matrix. The magnitude of spatial interdependency is measured by *Rho*, and W_i states how observations are related to one another.

The SEM model considers that error terms or residuals of the OLS are spatially correlated [111]. Hence, error terms are divided into a random error term and an error term [65]. The following equation expresses the SEM model:

$$y_i = \beta_\circ + X_i\beta + \lambda W_i\xi_i + \varepsilon_i \ , \quad i = 1,\ldots\ldots, n$$

Where, at Ward i, ξ_i is the error's spatial component; the intensity of correlation between these components is expressed by λ (*Lamda*); uncorrelated error term (spatially) is expressed by ε_i; W_i is the spatial weights matrix; $W_i\xi_i$ indicates the magnitude of the correlation between the spatial component of the errors with each other for nearby observations. This model accounts for spatial autocorrelation in error through the spatial weights matrix.

In this study, these two models were developed using the GeoDa software incorporating first-order Queens' contiguity weight matrix. This study used the same significant independent variables of the OLS model to calibrate these two models for comparison.

To decide the better modeling approach between the SLM and SEM, it is necessary to check the results of Lagrange Multiplier (LM)-lag and Lagrange Multiplier (LM)-error tests of the OLS model [109]. If the result of the LM-lag is found to be significant and LM-error is not, then it should be appropriate to develop the SLM model. The SEM model should be developed when the result of LM-error is significant while LM-lag is not. If both LM-lag and LM-error are significant, the Robust LM-lag and Robust LM-error results need to be checked. If the result of Robust LM-error is significant and Robust LM-lag is not, then the SEM model should be developed. The SLM model should be developed if the result of the Robust LM-lag is significant while Robust LM-error is not. If both Robust LM-lag and

Robust LM-error are significant, it is necessary to look at the one with a lower p-value [109].

3.3.1.4 Checking the presence of spatial heterogeneity in the OLS model

This study used the Breusch-Pagan test to assess the presence of spatial non-stationarity (spatial heterogeneity) in the residuals of the OLS model. This characteristic indicates that the relationships between the dependent and independent variables vary over the geographical space [33]. A significant result of this test indicates the presence of spatial non-stationarity, which highlights the necessity for developing local spatial regression models such as GWR and MGWR [61, 62].

3.3.1.5 Specification and estimation of geographically weighted regression (GWR) and multiscale GWR (MGWR) models

Unlike global regression models' estimated parameters that are the same for the whole study area, the GWR is used to develop local models for each location separately to show the spatial varying association between dependent and independent variables [69]. The GWR model is generally expressed by the following equation [65, 112]:

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} X_{ik} + \varepsilon_i \,, \quad \mathrm{i} = 1,\ldots\ldots\ldots, n;\ k = 1,\ldots\ldots\ldots, p$$

Where, at Ward i, K is the built environment-related independent variable within each ward, which varies from variable 1 to variable p; the value of K^{th} independent variable is expressed by X_{ik}; β_{ik} is the local regression coefficient for K^{th} independent variable; intercept parameter is expressed by β_{i0}, and ε_i is the random disturbance.

The GWR modeling technique can capture the spatial variations in the relationships between the dependent variable and independent variables considering a constant spatial scale (a global bandwidth) across the study area [62]. However, this approach might not be appropriate when relationships between dependent and independent variables vary at several spatial scales [69]. The MGWR modeling technique can solve this problem by developing local models for each location separately to explore the local associations between the dependent and independent variables at various spatial scales [71]. This modeling technique can incorporate different bandwidths (local bandwidth) across the study area, and the general form of this model is as follows [65]:

$$y_i = \sum_{k=0}^{p} \beta_{bwk} X_{ik} + \varepsilon_i \,, \quad i = 1,\ldots\ldots\ldots,\text{n} \;\; ; k = 1,\ldots\ldots\ldots, p$$

Where all the parameters are as same as the equation of the GWR model except β_{bwk}. The bandwidth parameter is expressed by β_{bwk}, which is used for the estimation of the k^{th} relationship. A more detailed discussion on GWR and MGWR could be found in the study of Comber, Brunsdon, Charlton, Dong, Harris, Lu, Lü, Murakami, Nakaya and Wang [62] and Fotheringham, Yang and Kang [71].

In this study, these two models were calibrated using MGWR 2.2 software incorporating the same significant independent variables of the OLS model. This study used the fixed kernel because the size of the wards was moderately uniform in the study area. In addition, this study used the "Golden Section" for bandwidth searching and "*AICc*" as optimization criteria to develop these two local models.

To identify the better modeling approach between the GWR and MGWR, it is necessary to check the bandwidths of the MGWR model. If the bandwidths for all the independent variables of the MGWR model show a global trend (tend to be equal), then the GWR modeling approach suits better. On the other hand, if the bandwidth(s) of one or more independent variables deviate from the global bandwidth and show a local trend, then the MGWR modeling approach would be appropriate [62].

3.3.1.6 Comparison of all the estimated models

After developing all the five models, this study evaluated their performance based on the statistics of R^2, *adjusted* R^2, Akaike information criterion (*AIC*), corrected Akaike information criterion (*AICc*), and *CN*. It is worthy to mention that the GeoDa does not provide *adjusted* R^2 and *AICc* statistics for SLM and SEM. Therefore, these two models were compared with others based on *AIC* statistics. Besides, spatial autocorrelation is generally not a problem for a well-specified GWR or MGWR model [61]. Therefore, this study measured the presence of spatial autocorrelation in residuals of the developed SLM, SEM, GWR, and MGWR models through Moran's I method for further comparison.

3.3.2 Modeling Pedestrian Crash Severity

This study developed a GLR and a GWLR model. Here, the severity of a pedestrian crash was used as the dependent variable, which had two categories: fatal and non-fatal (merging grievous, simple injury, and motor collision levels into the non-fatal category due to their lower frequency as well as for simplicity). **Table 3-2** shows the independent variables for developing the model.

3.3.2.1 Specification and estimation of binary logistic regression (BLR) model

As the dependent variable had two categories, this study used binary logistic regression (BLR) as GLR for modeling. A BLR model was developed through a stepwise forward procedure using Statistical Package for the Social Sciences (SPSS) software.

The BLR is a modeling technique that estimates the relationships between a binary nature dependent variable with multiple independent variables [113]. This model cannot explore spatial variation in the relationships and estimates a single coefficient for each independent variable for the whole study area [114]. The BLR model can be defined according to the following equation.

$$ln\left(\frac{P}{1-P}\right) = \alpha_0 + \beta_1 x_1 + \beta_2 x_2 + \ \dots\dots\dots\dots + \beta_i x_i$$

Where, $ln\left(\frac{P}{1-P}\right)$ is the probability of fatal crash occurrence, intercept is expressed by α_0, and β_i is the coefficient of the x_i independent variable.

3.3.2.2 Specification and estimation of geographically weighted logistic regression (GWLR) model

On the other hand, the GWLR method can explore spatial variation in the relationships between dependent and independent variables by developing a local model for each observation [81, 83]. For developing a local model in an observation location, neighboring observations are also included in the modeling process.

Bandwidth size decides the number of neighboring observations, which will be considered for developing each local model [80]. There are two types of bandwidth: fixed distance (specify considering distance around the modeled observation) and adaptive distance (specify the number of neighboring observations to consider around modeled observation). Heavier weights are given to the observations near the modeled observation point than those located further away [80, 115]. The number of developed local models through the GWLR technique is equal to the number of total observations. Therefore, a coefficient is estimated for each independent variable for an observation. The coefficients of all the local models collectively express the spatially heterogeneous relationship between the dependent variable and each of the independent variables over the geographical space. The GWLR model can be expressed as the following equation.

$$ln(\frac{P_j}{1 - P_j}) = \sum_i \beta_i(u_j, v_j)x_{i,j} + \epsilon_j$$

Here, $ln(\frac{P_j}{1-P_j})$ is the probability of fatal crash occurrence for the jth observation; $x_{i,j}$and ϵ_j are the ith independent variable and error at jth observation, respectively. The x, y location of jth observation are expressed through (u_j, v_j). $\beta_i(u_j, v_j)$ is the coefficient for the ith independent variable at jth observation. For this study, adaptive bandwidth was used for GWLR modeling. Detail of bandwidth selection are described in **Section 5.2.2**. The GWLR models were developed using MGWR 2.2 software.

3.3.2.3 Comparison of the estimated BLR and GWLR models

In addition, the VIF was used to assess multicollinearity among the independent variables in the developed models. A VIF statistic of less than five indicates the absence of multicollinearity-related problems in the model. After developing the BLR and GWLR models, this study compared the deviance, percent deviance explained, and Akaike Information Criterion (AIC) statistics of the models to evaluate their performance.

3.3.3 Case analysis

After conducting macroscopic and microscopic analysis, for detail crash analysis, this study selected three wards having very high crash density and analyzed crash pattern in those wards. Those three wards are Dhanmondi, Saidabad, and Ramna.

3.4 Limitation of Work

3.4.1 Pedestrian Crash Occurrences Analysis

Like most studies on similar issues, this study also has some limitations. The first limitation of this study is the small sample size (n=92). In general, all the macroscopic studies were conducted with a small sample size (n < 100), which is a common limitation in these types of research [4]. The second inherent limitation is the use of aggregated data, which forced to reduce the detail. As a result, the individual-level data were inevitably lost. The third, fourth, and fifth unavoidable limitations are study-area specific. The third limitation is that some of the roads of Dhaka are located on the boundary of the wards. Therefore, some biased estimations could happen due to this. The fourth limitation is underreporting of crash data in Bangladesh as well as the use of relatively older crash data (2010-2015) in this study. At the time of data collection, it was found that crash data after 2015 was not available as those data were being processed by ARI, BUET. The fifth limitation is the absence of traffic flow data of Dhaka, which is generally considered an important independent variable and included in these types of models. However, some studies developed a macroscopic crash occurrence model without traffic flow data [4]. Also, traffic flow is heavily dependent on built environment factors. So, the effect of traffic flow might be covered through the built environment variables.

3.4.2 Pedestrian Crash Severity Analysis

There are several limitations present in the pedestrian crash severity analysis. First, underreporting of crash data, especially non-fatal crash data, is commonplace in Bangladesh, like in other developing countries. Therefore, missing a portion of the non-fatal crashes might cause inaccuracy in the estimated results. Second, this study could not consider several important crash-inducing factors (e.g., pedestrian characteristics, vehicle characteristics, speed factors, driver characteristics) due to data unavailability, missing data, and model simplicity. Considering those factors might improve the model explaining power. Third, the GWLR model estimates relationships between the dependent variable and all the independent variables using a single (global) bandwidth. However, it might be possible that the relationship between the dependent variable and each independent variable operates in different local bandwidths. If the GWLR model can estimate using several optimal bandwidths for each relationship between dependent and independent variables, the model performance could be significantly improved.

CHAPTER 4: EFFECTS OF BUILT ENVIRONMENT ON PEDESTRIAN CRASH OCCURRENCES

This chapter shows the analyses and results of the first objective: to explore the effects of the built environment on pedestrian crash occurrences at a macroscopic level. First, descriptive statistics are presented in a summarized way. Then, the estimation and results of the models are described in detail. Finally, a discussion on the results of the models as well as the implication of the results in planning are presented at the end portion of the chapter.

4.1 Descriptive Statistics

Descriptive statistics of all the dependent and independent variables are presented in **Table 4-1.** The results indicate that there were approximately 0.09 pedestrian crashes per hectare area in the study area on average. Pedestrian crash density varied enormously from ward to ward, ranging from zero crashes per hectare to 0.63 crashes per hectare (**Figure 4-1**).

Table 4-1: Descriptive statistics of dependent and independent variables for pedestrian crash occurrences analysis

Variable name	Mean	Std. dev.	Max	Min
Dependent variable				
Pedestrian crash density	0.09	0.12	0.63	0
Independent variable				
Demographic characteristics related factors				
Population density	834.81	593.91	3707.54	44.73
Job density	286.79	234.64	1000	13.71
Employed person density	364.58	364.48	2282	23.59
Land use characteristics related factors				
Residential land use density	0.372	0.30	0.83	0
Commercial land use density	0.014	0.04	0.21	0
Industrial land use density	0.008	0.05	0.49	0
Mixed land use density	0.245	0.29	0.87	0
Recreational land use density	0.026	0.05	0.34	0
Institutional land use density	0.054	0.10	0.52	0
Roadway and traffic characteristics related factors				
Local road density	260.2	154.1	1291.2	23.4
Secondary road density	22.7	26.5	144	0
Primary road density	11.3	14.5	84.8	0
Minor intersection density	1.46	1.03	7.2	0.2
Major intersection density	0.03	0.03	0.2	0
Link node ratio	0.77	0.11	1.05	0.6
Non-motorized modes share	62.1	14.1	91	28.6
Public mode share	23.5	9.4	43.9	3.2
Private modes share	7.9	5.3	22.9	1.3
Paratransit modes share	6.3	2.7	14.5	1.1

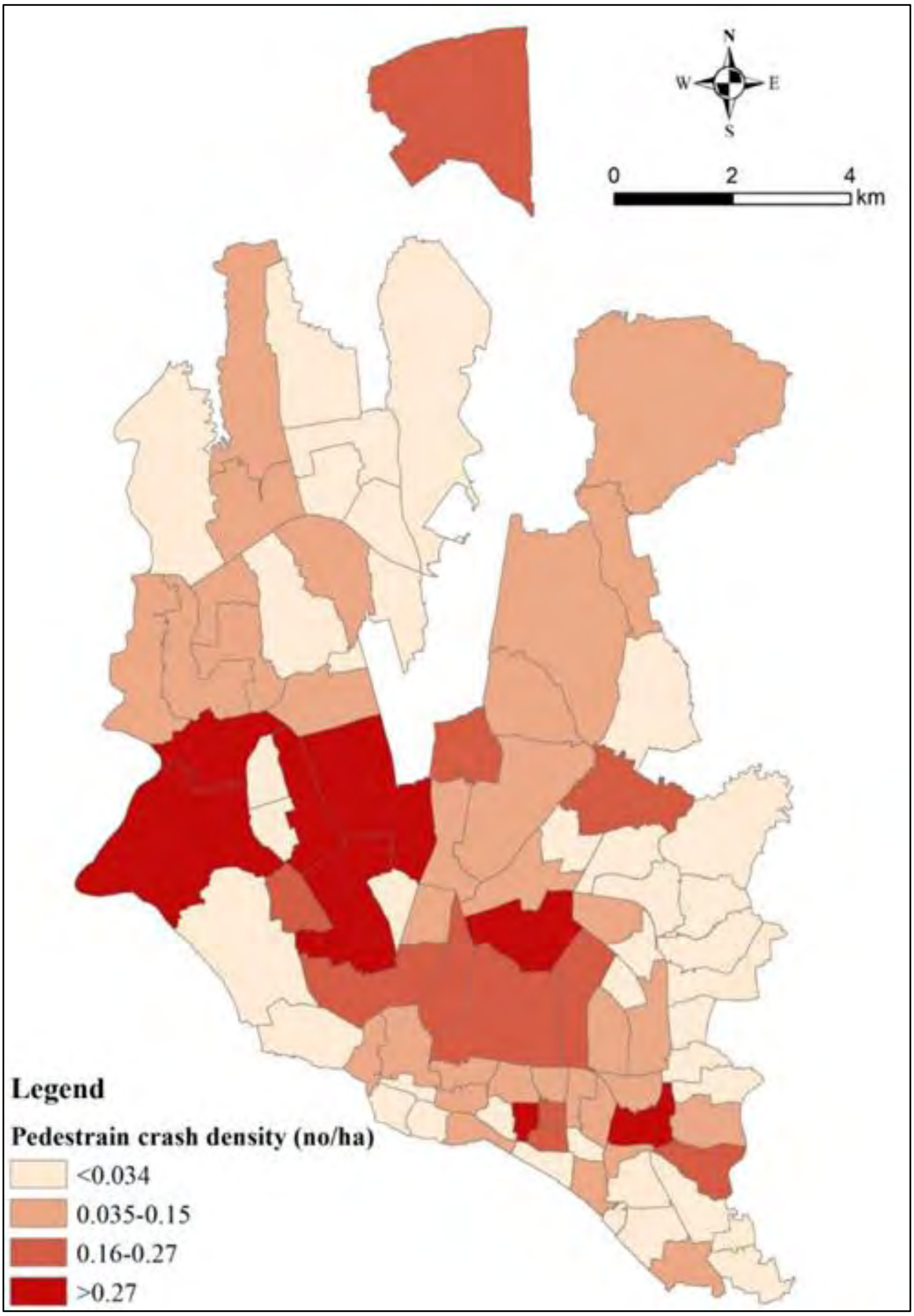

Figure 4-1: Spatial distribution of pedestrian crash density

4.2 Results of the Estimated Models

4.2.1 Ordinary Least Squares (OLS) model

The results of the estimated OLS model are presented in **Table 4-2**. Six independent variables were found to be statistically significant: employed person density, mixed land use density, recreational land use density, primary road density, major intersection density, and non-motorized modes share. **Figure 4-2** shows the spatial distribution of the significant independent variables. Multicollinearity among the independent variables in the model was absent as all the *VIF* statistics were less than two, and the *CN* of the model was below 30. The model statistics show that the overall model was statistically significant (p < 0.01). The model had an R^2 value of 0.6348, indicating that the six significant independent variables could explain 63.48% variation in the pedestrian crash density across Dhaka. All the significant variables had a positive relationship with pedestrian crash density except non-motorized modes share (**Table 4-2**).

Table 4-2: Results of the OLS model

Factors	Coefficient	Std. error	*t*-statistic	*p*-value	VIF
Intercept	-0.1411	0.0732	-1.92	0.057	
Employed person density	0.0001	0.00002	4.54	-0.000*	1.4
Mixed land use density	0.2329	0.0686	3.39	0.001*	1.7
Recreational land use density	2.8698	1.0043	2.85	0.005*	1.3
Primary road density	0.0032	0.0006	5.44	0.000*	1.3
Major intersection density	0.8985	0.2111	4.25	0.000*	1.1
Non-motorized modes share	-0.0012	0.0006	-2.07	0.040**	1.2
Model statistics: F(6, 82) = 23.766, p = 0.000, R^2 = 0.6348, *Adjusted* R^2= 0.608, *AIC*= –213.419, *AICc*= –209.61,Condition Number (*CN*)= 26.42					

*significant at 99% confidence level, ** significant at 95% confidence level

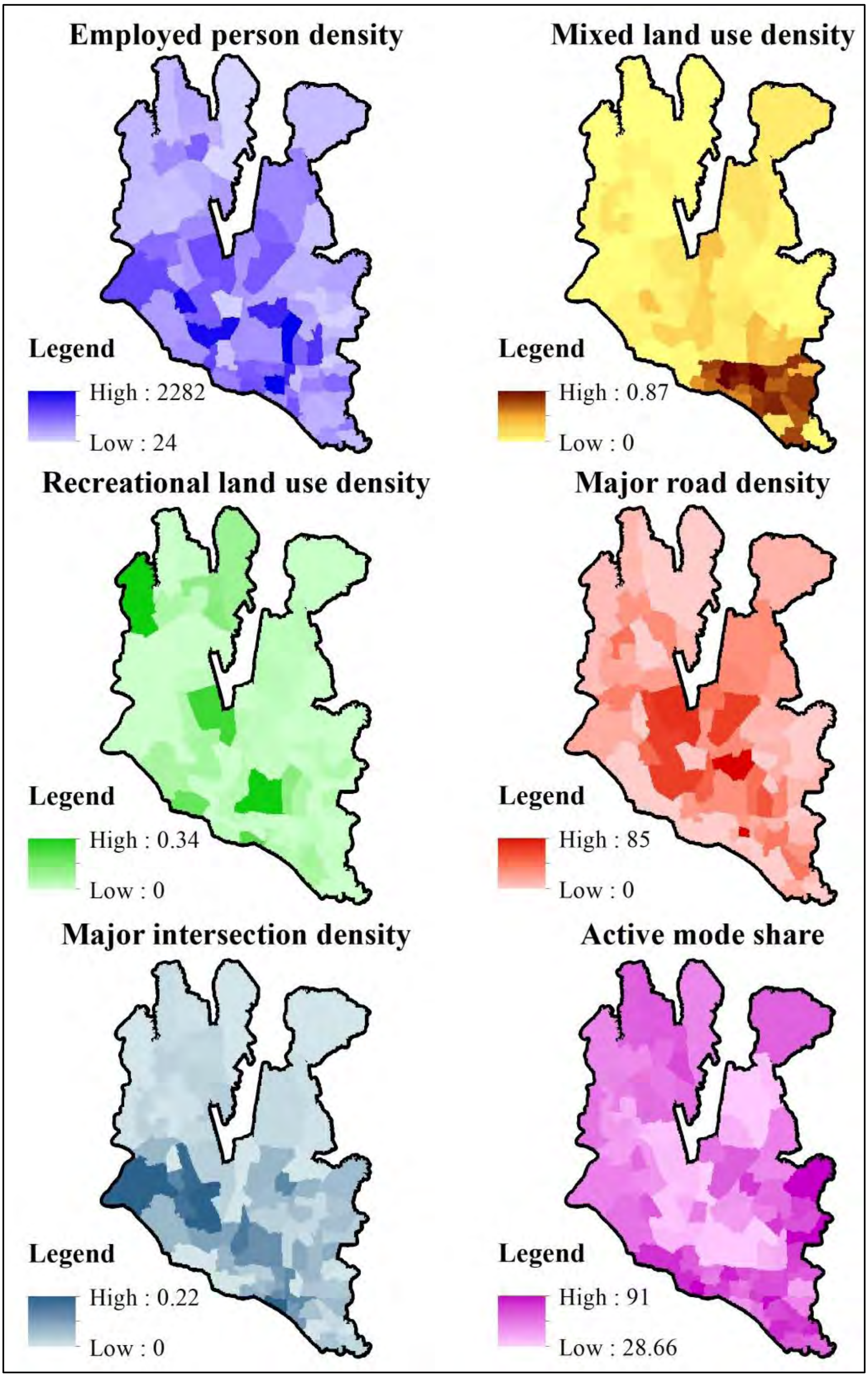

Figure 4-2: Spatial distribution of the significant independent variables of the OLS model

To check if the results of the OLS model are acceptable, it was necessary to examine whether spatial autocorrelation or spatial non-stationarity was found in the model. The Moran's I diagnostics of residual for the model was not found to be statistically significant (*MI*= 0.061, $p > 0.05$) (**Table 4-3**). This result confirmed the absence of spatial autocorrelation in the model. On the other hand, this study used the Breusch-Pagan (BP), Koenker-Bassett (KB), and White tests to determine whether the residuals had a non-constant variance (spatial non-stationarity) across the wards. Results of all the spatial non-stationarity diagnostics were found to be statistically significant ($p < 0.01$), indicating that associations between pedestrian crash density with at least one or more independent variables were non-stationarity (**Table 4-3**). This result highlights that the OLS technique was not the best approach for modeling the pedestrian crash density. Therefore, the modeling approach needed to be changed. Under the circumstances, the local spatial regression modeling approaches (e.g., GWR and MGWR) usually perform better than the OLS since these approaches can explore the local relationships and account for spatial non-stationarity characteristics.

Table 4-3: OLS diagnostics

Test	*df*	MI	Value	*p*-value
Diagnostics for spatial autocorrelation of residual				
Moran's I		0.061	1.3356	0.181
Lagrange Multiplier (lag)	1		0.171	0.679
Robust LM (lag)	1		0.079	0.778
Lagrange Multiplier (error)	1		0.758	0.383
Robust LM (error)	1		0.666	0.414
Diagnostics for spatial non-stationarity of residual				
Breusch-Pagan (BP) test	6		31.804	0.000*
Koenker-Bassett (KB) test	6		22.226	0.001*
White test	27		48.312	0.007*
*statistically significant at 99% confidence interval, ** statistically significant at 95% confidence interval				

4.2.2 Spatial Lag Model (SLM) and Spatial Error Model (SEM)

Since there was an absence of spatial autocorrelation in residuals of the OLS model, it was not necessary to develop the SLM and SEM. However, these two models were developed for comparison purposes in this study. **Table 4-4** shows the summary results of the SLM and SEM. All the six independent variables of the OLS were found to be significant in both models. The coefficients of the independent variables show a positive association with the dependent variable except non-motorized modes share. The R^2 and *AIC* statistics of these two models were almost similar to the statistics of the OLS model (**Table 4-2** and **Table 4-4**). This finding indicates that these two models failed to deliver better results than the OLS model due to the absence of spatial autocorrelation. However, the *MI* statistics show that these two models minimize the magnitude of spatial autocorrelation more than the OLS model (**Table 4-3** and **Table 4-4**). Both *Rho* of the SLM and *Lamda* of the SEM were insignificant ($p > 0.05$). Finally, the results of the Breusch-Pagan (BP) test were found to be significant ($p < 0.01$), indicating the presence of spatial non-stationarity characteristics in both models. These two global spatial models failed to address the spatial non-stationarity characteristics of the OLS model, which emphasized the need to develop local spatial regression models.

Table 4-4: Results of SLM and SEM

Variable	Coefficient		Std. error		*z*-value		*p*-value	
	SLM	SEM	SLM	SEM	SLM	SEM	SLM	SEM
Intercept	-0.149	-0.143	0.073	0.071	-2.043	-2.031	0.040	0.042
Employed person density	0.0001	0.0001	0.00002	0.00002	4.737	4.76	0.000*	0.000*
Mixed land use density	0.234	0.232	0.066	0.067	3.552	3.477	0.000*	0.000*
Recreational land use density	2.83	2.794	0.965	0.966	2.932	2.892	0.003*	0.003*
Primary road density	0.0032	0.0032	0.0005	0.0005	5.663	5.644	0.000*	0.000*
Major intersection density	0.884	0.93	0.208	0.21	4.252	4.443	0.000*	0.000*
Non-motorized modes share	-0.0012	-0.0012	0.0006	0.0006	-2.017	-2.058	0.043	0.039
Rho	0.0434		0.112		0.388		0.697	
Lamda		0.142		0.152		0.939		0.347
SLM: R^2= 0.635, *AIC*= -211.578, MI= 0.041, Breusch-Pagan (BP) test- BP= 33.386, *p*-value= 0.000								
SEM: R^2= 0.639, *AIC*= -214.201, MI= 0.005, Breusch-Pagan (BP) test- BP= 33.832, *p*-value= 0.000								

*statistically significant at 99% confidence interval, ** statistically significant at 95% confidence interval

4.2.3 Geographically Weighted Regression (GWR) and Multiscale GWR (MGWR)

To address the problem of spatial non-stationarity of the OLS model, this study developed two local regression models: GWR and MGWR. Though multicollinearity was absent in the global model, it could be present in the local models. Therefore, local collinearity diagnostics were carried out in both GWR and MGWR models. Both models' highest local *CN* statistics were found below 30, indicating the absence of multicollinearity in the local models. **Table 4-5** summarizes the results of both models. The *adjusted* R^2 (0.604), *AIC* (–211.447), and *AICc* (–209.613) of the GWR model were found similar to the OLS model (*adjusted* R^2 = 0.608, *AIC*= –213.419, and *AICc*= –209.61). Besides, this study found a much higher *adjusted* R^2 (0.726) and a much lower *AIC* (-235.173) and *AICc* (–223.812) for the MGWR model than the OLS model. In addition, the MGWR model also minimized the magnitude of the spatial autocorrelation in the residuals from the OLS model (**Table 4-5**). All these statistics indicate that although the GWR model performed similarly to the OLS model, a large improvement was found in the MGWR model's performance.

The interquartile range (*IQR*) indicates that the GWR model coefficients showed lower variation than the MGWR model for the primary road density and major intersection density (**Table 4-5**). The reason behind the lower variation could be that the global bandwidth of the GWR model (bandwidth= 35018m) was much wider than the bandwidths for these two variables in the MGWR model (bandwidth of primary road density = 1112m, and major intersection density= 3848m). However, for the rest of the independent variables, variation in the coefficients was almost similar in both GWR and MGWR models. The reason could be that the global bandwidth of GWR was found similar to the local bandwidths for the other independent variables in the MGWR model (approximate bandwidth= 35021 m).

In the GWR model, all the independent variables had very low *IQR* statistics, indicating that relationships between these variables with pedestrian crash density did not vary much within the study area (**Table 4-5**). In other words, the relationships between the dependent variable and independent variables were global. In the case of the MGWR model, *IQR* statistics were found higher for primary road density (median= 0.0025 and *IQR*= 0.0016) and major intersection density (median=

0.54 and *IQR*= 0.287), indicating the presence of strong spatial variation (**Table 4-5**). Therefore, these relationships were local along with their bandwidths. Apart from these two variables, other independent variables of the MGWR model showed global relationships within the study area, as indicated by *IQR* statistics (**Table 4-5**).

Figure 4-3, **Figure 4-4**, and **Figure 4-5** show the spatial distribution of the coefficients and significance levels of the independent variables of the GWR and MGWR models. Comparison of the coefficients would be helpful to develop a clear understanding of the spatial variation of the relationships as well as the importance of considering spatial scale variation. The coefficients of employed person density, mixed land use density, recreational land use density, and non-motorized modes share did not vary much within the study area and were found to be significant in all areas in the both GWR and MGWR models (**Figure 4-3**, **Figure 4-4**, and **Figure 4-5**). These variables were estimated through a global bandwidth in GWR and MGWR models. The relationships between pedestrian crash density with primary road density and major intersection density varied locally within the study area according to the MGWR model (**Figure 4-4** and **Figure 4-5**). Primary road density had a strong relationship with pedestrian crash density in the middle-western (Gabtoli) part of Dhaka and had a moderately strong relationship in the south-eastern (Jatrabari and Sayedabad) part (**Figure 4-4**). However, the relationship was not found to be significant in most of the northern parts of the study area (**Figure 4-4**). In addition, the spatial distribution of the coefficients of major intersection density showed a clear pattern as per the MGWR model. The coefficients were higher in the north-western part and declined towards Dhaka's south-eastern, eastern, and north-eastern parts (**Figure 4-5**). This relation was not significant in most of the eastern parts of the study area. Contradictorily, the relationships between pedestrian crash density with primary road density and major intersection density were global as per the GWR model (**Figure 4-4** and **Figure 4-5**).

Table 4-5: Coefficient, bandwidth, and models statistics of the GWR and MGWR models

	GWR (Bandwidth (BW)=35018 m)				MGWR				
Variables	**1Q**	**Med**	**3Q**	**IQR**	**1Q**	**Med**	**3Q**	**IQR**	**BW (m)**
Intercept	–0.141421	–0.141181	–0.141003	0.0004	-0.086738	-.086728	-0.086719	0	35021
Employed person density	0.000111	0.000111	0.000111	0	0.000123	0.000123	0.000124	0	35018
Mixed land use density	0.232681	0.232911	0.233191	0.0005	0.152602	0.152617	0.152631	0	35021
Recreational land use density	2.871986	2.873784	2.875835	0.0038	2.138127	2.139147	2.140039	0.0019	35021
Primary road density	0.003250	0.003254	0.003259	0	0.002107	0.002509	0.003720	0.0016	1112
Major intersection density	0.892968	0.896205	0.901302	0.0083	0.473215	0.540172	0.760698	0.2875	3848
Non-motorized modes share	-0.001248	-0.001247	-0.001246	0	-0.000990	-0.000989	-0.000989	0	35021
Model Statistics									
R^2	0.636				0.783				
Adjusted R^2	0.604				0.726				
AIC	-211.447				-235.173				
AICc	-209.613				-223.812				
MI	0.061				-0.045				
1Q = 1st quartile, Med = median, 3Q = 3rd quartile, IQR = interquartile range									

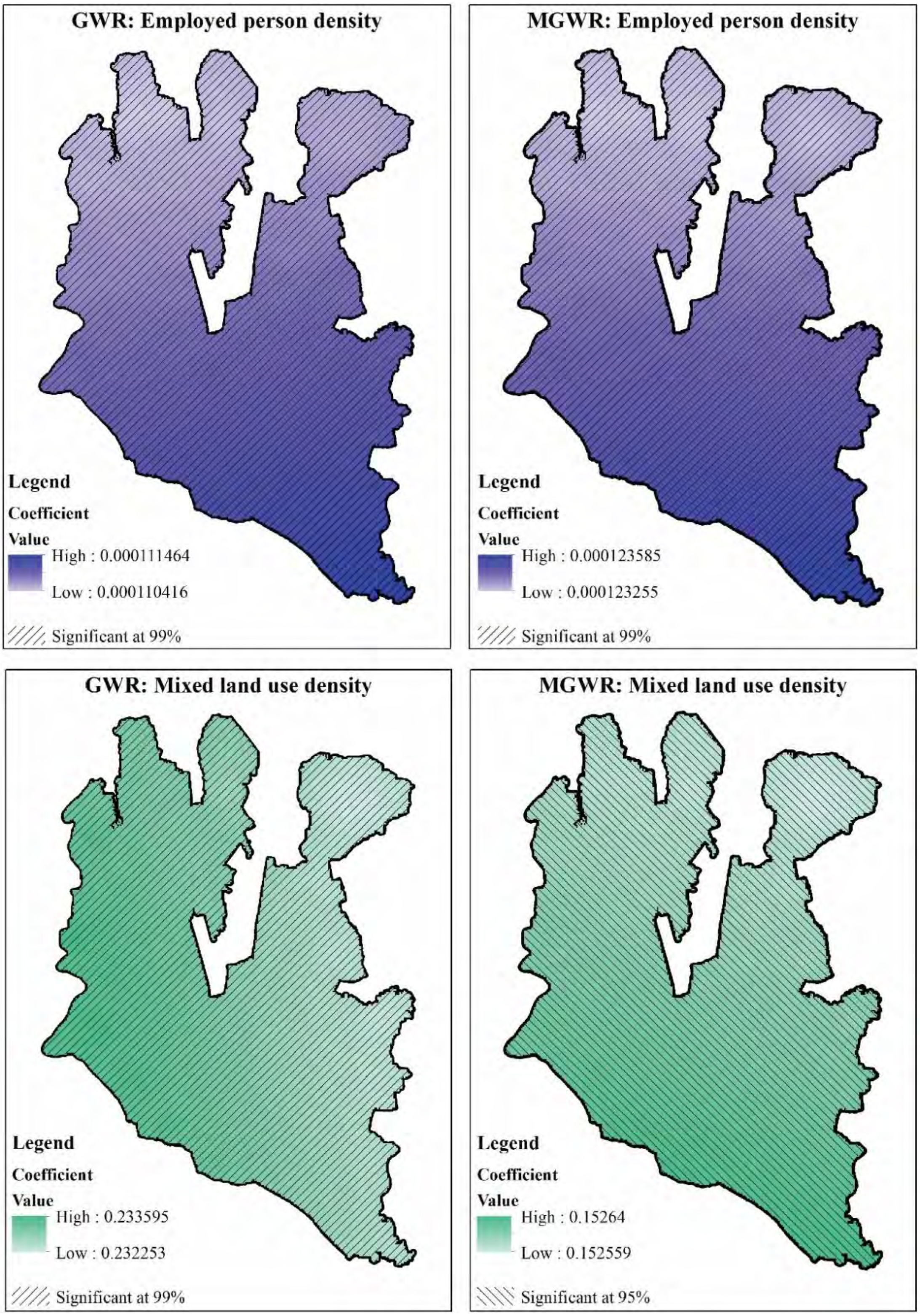

Figure 4-3: The effects of employed person density (above) and mixed land use density (below) in describing pedestrian crash density using GWR (left) and MGWR (right) models

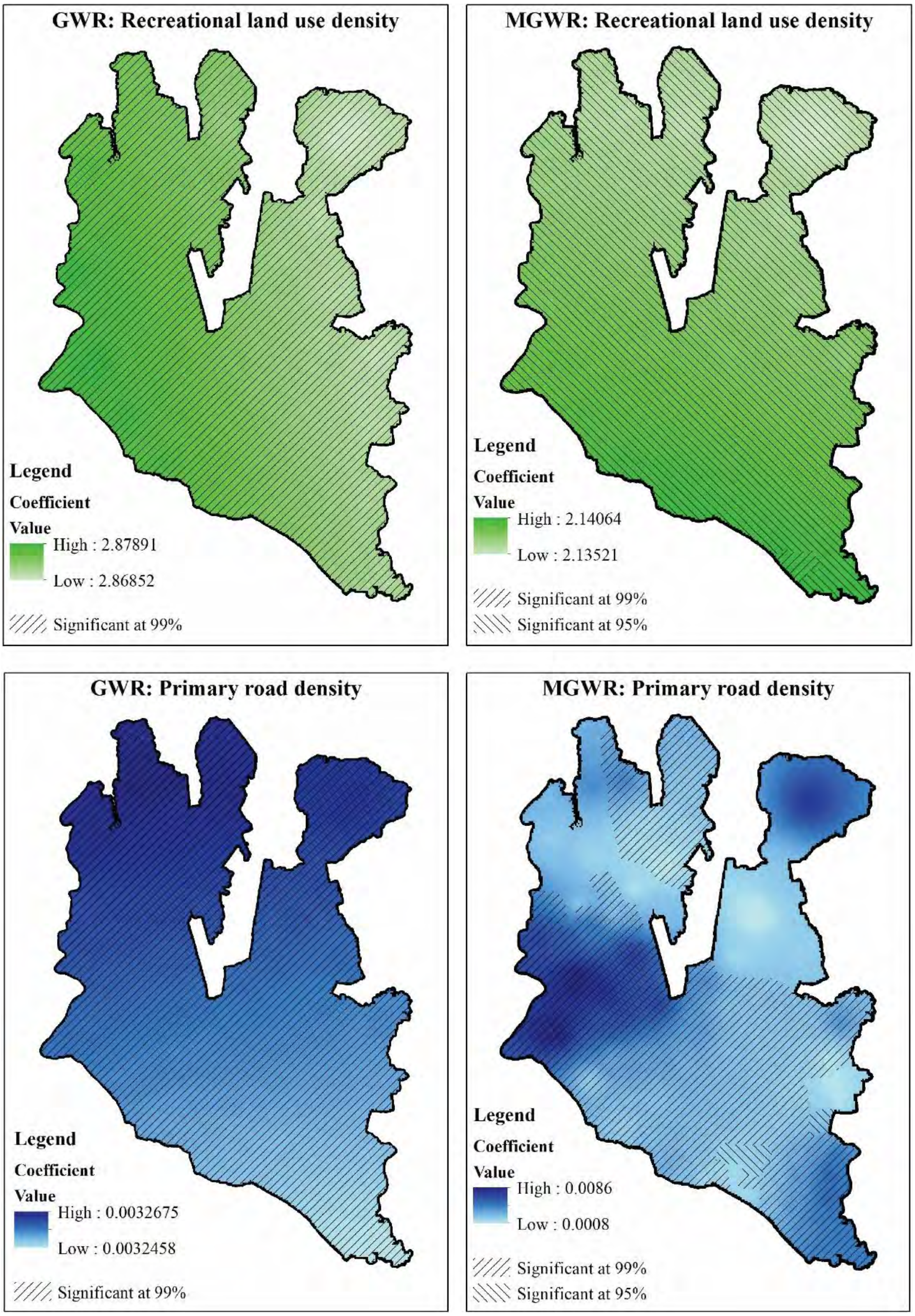

Figure 4-4: The effects of recreational mixed land use density (above) and primary road density (below) in describing pedestrian crash density using GWR (left) and MGWR (right) models

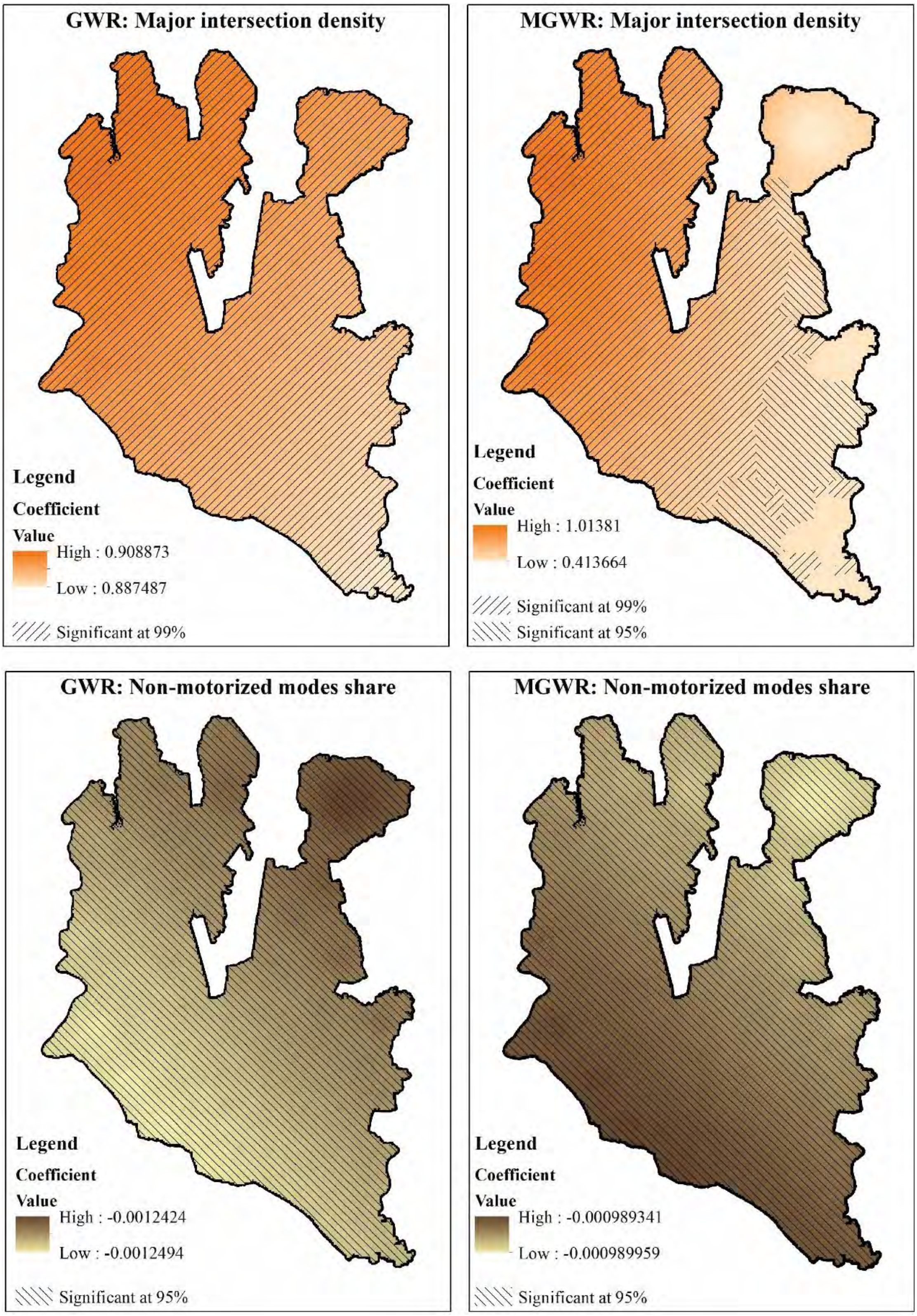

Figure 4-5: The effects of major intersection density (above) and non-motorized modes share (below) in describing pedestrian crash density using GWR (left) and MGWR (right) models

4.3 Discussion

4.3.1 Model Estimation

This study explored the effects of the built environment on pedestrian crash density in Dhaka, Bangladesh. First, a global non-spatial OLS model was estimated, ensuring that multicollinearity was not an issue in the model. Six independent variables were found to be significant in the model. This study then developed two global spatial regression models: SLM and SEM. These models can consider the issue of spatial autocorrelation. However, the residuals of the OLS model were not spatially correlated. As a result, using the SLM and SEM was not necessary for this study, and the performance of these two models was not better than the OLS model.

The presence of spatial non-stationarity in the residuals of the OLS model emphasized the need to develop local spatial regression models. This study developed two local spatial models: GWR and MGWR, to explore the local relationships between the independent variables and pedestrian crash density. From the results, it could be concluded that the GWR model failed to explore the local relationships since this technique considered a global bandwidth for all the independent variables to explore their relationships with pedestrian crash density. On the other hand, the MGWR model used variable-specific bandwidths. This facilitated capturing the local relationships between pedestrian crash density with primary road density and major intersection density. Therefore, all the model evaluation statistics vastly improved for the MGWR model compared to the GWR model. The R^2 and *adjusted* R^2 statistics increased in the MGWR model compared to the OLS model by 14.8% and 11.8%, respectively. The *AIC* and *AICc* statistics of the MGWR were found much lower than the OLS model suggesting a considerable improvement. The *MI* statistics were also found lower for the MGWR model than the OLS model indicating the model was able to curb the spatial autocorrelation-related problem. Besides, the model evaluation statistics were found to be similar in both GWR and OLS models, indicating no improvement in the GWR model. Therefore, the MGWR method was found to be the best approach for modeling pedestrian crash density in this study. This result was found consistent with the results of the previous studies in other disciplines where the researchers compared the performance of non-spatial and spatial regression models [e.g., 65, 69].

4.3.2 Model Findings and Implications for Planning

4.3.2.1 Density related factors

Among the density variables, employed person density was statistically significant in all the developed models. This variable had a positive and homogeneous relationship with pedestrian crash density throughout the study area. This result was consistent with previous studies [e.g., 8, 16]. A large number of the people of cities in developing countries, including Dhaka, choose public or paratransit modes as primary mode and walking as their access and egress mode while making a commuting trip [105, 116]. Therefore, conflicts at transit stations (bus stop/ paratransit station) between vehicles and pedestrians are unavoidable as the stations are not well designed and well designated, as well as for overcrowding [117, 118]. In most cases, people need to wait and access the primary mode standing on the primary road, which makes them highly vulnerable [119]. In general, the number of commuting trips was higher in wards having higher employed person density; as a result, more pedestrian crashes occurred in those wards. Implementation of a proper integrated multi-modal transport plan could be helpful to reduce conflicts and improve pedestrian safety conditions in wards having high employed person density.

4.3.2.2 Land use characteristics related factors

This study found density of mixed and recreational land use significant in all the developed models. Pedestrian crash density was higher in wards with higher mixed land use density. This result was found consistent with the results of previous studies [17, 45]. However, the finding was the opposite in the study of Wang and Kockelman [19]. Several land use types are placed in the same zone in a mixed land use area. Different types of land use attract different modes: both motorized and non-motorized, leading to a high volume of motorized and non-motorized traffic [4]. In developing countries, mixed land use developed spontaneously rather than in a planned way. Therefore, the movement of a high volume of heterogeneous modes in an unplanned ward increases conflicts between travel modes and pedestrians, and consequently, increasing crash density [45]. In high mixed land use wards, reducing speed and volume of the motorized vehicles, increasing non-motorized modes share, segregating the movements of motorized and non-motorized modes, and ensuring safe access to destinations could improve pedestrian safety. Provision of proper pedestrian facilities, implementation of travel demand management-related strategies, as well as appropriate design of streets could be helpful to achieve the above-mentioned performance in mixed used wards.

Pedestrian crash density was also higher in wards having high recreational land use density. This result was found consistent with the study of Ukkusuri, Miranda-Moreno, Ramadurai and Isa-Tavarez [15]. However, opposite results were found in the study of Osama and Sayed [8] and Ukkusuri, Hasan and Aziz [7]. A possible explanation could be that pedestrians near the recreational area are less attentive on the road due to focusing on recreational activities, physical exercises, and gossiping with other, which makes the pedestrian vulnerable near the recreational area, and leads to increase pedestrian crashes. Further studies need to be conducted to explore pedestrian behavior and vulnerability near the recreational area. Pedestrian awareness-raising programs should be taken near the recreational area. Proper street design is also necessary to control the speed of the vehicles near the recreational area to reduce crash exposure.

4.3.2.3 Roadway and traffic characteristics related factors

Three variables related to roadway and traffic characteristics were found to be significant in this study: primary road density, major intersection density, and non-motorized modes share. Primary road density had a positive relation with pedestrian crash density. Pedestrian crash density was higher in the wards with higher primary road density. This result was consistent with previous studies [e.g., 8, 19]. The primary road could be a proxy variable of traffic volume [4], which was not incorporated in this study due to the unavailability of the data. Generally, primary roads can be characterized as high vehicular traffic volume and high vehicular speed [8]. These roads also provide access to the low-speed traffic in the surrounding land use [4]. Since the condition of the pedestrian facilities in the primary roads is not good enough (e.g., blockage of the footpath, unusable condition of the footpath, absence of footpath and proper crossing facilities), pedestrians need to share the primary road with vehicles in Dhaka [6]. Therefore, conflicts between pedestrians and high-speed traffic increase, resulting in increasing pedestrian crash density. In this study, this relationship was local in the MGWR model. The association was found stronger in Gabtoli, Sayedabad, and Jatrabari areas. This could be because, through these areas, two national highways connect Dhaka with other parts of the country. In addition, two largest bus terminals are also located there. A high volume of heavy vehicles move through these highways, and many passengers arrive at and depart from these terminals. Therefore, a large number of pedestrian crashes occurred on these primary roads. This relationship was not found significant in most of the north part of the city. The possible explanation could be the presence of fewer primary roads in those wards (**Figure 4-4**). To address the situation, retrofitting the primary roads and surrounding areas is necessary to separate pedestrians and motorized traffic. Also, vehicle operating speed needs to be controlled to improve pedestrian safety. In addition, a complete street scheme could be taken on the primary roads of Dhaka. Bypass roads could be constructed to separate inter-city traffic from intra-city traffic, and consequently, reduce traffic volume on the primary roads. Close attention should be given in areas having strong impact of primary road density on pedestrian crash density.

It was also found that pedestrian crash density increased in the wards having higher major intersection density. This result was found consistent with previous studies indirectly [e.g., 14, 15]. Those studies showed that pedestrian crashes occurred more in complicated intersections. In major intersections, traffic volume was found to be very high. Furthermore, a large number of pedestrians crossed the road at major intersections where the condition of pedestrian crossing facilities is not good enough in the context of developing countries [120]. Since traffic signals are not functional at major intersections of Dhaka and traffic police control these intersections focusing on vehicle traffic, non-compliance behaviors are commonplace at the major intersections by both pedestrians and drivers [97]. Besides, in some major intersections, foot overbridges are provided to facilitate pedestrians to cross the road safely. However, many people are reluctant to use those foot overbridges to cross the road [121]. As a result, conflicts increase at major intersections, and consequently, pedestrian crash increases. This relationship was also found heterogeneous throughout the study area. A strong association was found in the middle and north-western parts of the city. It could be because of the presence of major arterial roads and national highways in those parts, which create several vulnerable intersections where crashes occurred more frequently (**Figure 4-5**). Installing traffic signals considering pedestrian needs, providing proper pedestrian crossing facilities, pedestrian safety campaign to encourage pedestrians to adopt safe crossing behavior, and prioritizing pedestrians at major intersections could decrease conflicts and improve pedestrian safety.

Finally, non-motorized modes share had a negative and homogeneous effect on pedestrian crash density. This result was not consistent with the study of Chen and Zhou [14]. Increasing non-motorized mode share reduces the number of conflicts with the motorized vehicle in that ward, and subsequently, pedestrian crash density is reduced. Therefore, each ward could encourage the non-motorized mode to reduce pedestrian crashes. It could be achieved by restructuring the urban built environment by implementing appropriate planning strategies, such as TOD, smart growth, and compact development, and adopting complementary traffic management measures.

CHAPTER 5: EFFECTS OF BUILT ENVIRONMENT ON PEDESTRIAN CRASH SEVERITY

This chapter covers the second objective of this thesis: to explore the effects of the built environment on pedestrian crash severity at a microscopic level. At the beginning of the chapter, descriptive statistics are summarized. After that, the estimation and results of the global and local models are described in detail. At the end of the chapter, discussion on the results of the models as well as the implication of the results for planning are presented.

5.1 Descriptive Analysis

Out of 1,166 pedestrian crashes, the severity level of 924 crashes (79.2%) were fatal. The rest of the 20.8% crashes were non-fatal, indicating a significantly higher number of fatal crashes than non-fatal crashes reported in the study area. This study shows the spatial distribution of fatal and non-fatal crashes in **Figure 5-1** and the descriptive statistics of independent variables in **Table 3-2**.

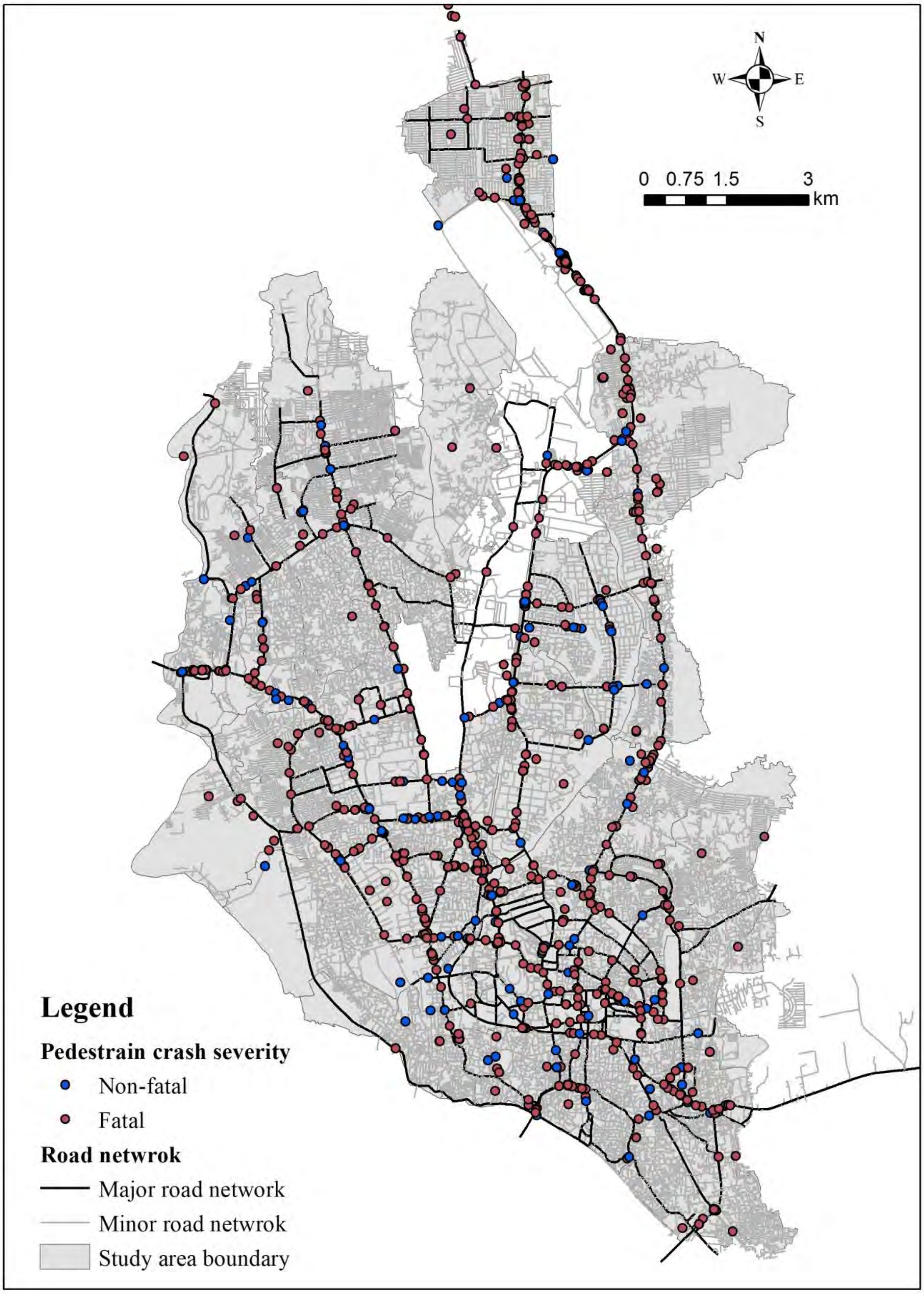

Figure 5-1: Location of pedestrian crashes by their severity

Table 5-1: Descriptive statistics of independent variables for pedestrian crash severity analysis

Factors	Level of severity		Total
	Fatal [N (%)/μ (σ)]	Non-fatal [N (%)/μ (σ)]	
Natural environment characteristics			
Season			
Summer	295 (78.9%)	79 (21.1%)	374 (32.1%)
Rainy season	317 (81.7%)	71 (18.3%)	388 (33.3%)
Winter	312 (77.2%)	92 (22.8%)	404 (34.6%)
Time of day			
Day	563 (76.7%)	171 (23.3%)	734 (63.0%)
Night	361 (83.6%)	71 (16.4%)	432 (37.0%)
Light condition			
Well-lit	858 (78.3%)	238 (21.7%)	1096 (94.0%)
Unlit	66 (94.3%)	4 (5.7%)	70 (6.0%)
Weather condition			
Good	896 (78.9%)	239 (21.1%)	1135 (97.3%)
Adverse	28 (90.3%)	3 (9.7%)	31 (2.7%)
Built environment characteristics			
Roadway characteristics at the crash location			
Location			
Non-intersection	664 (79.4%)	172 (20.6%)	836 (71.7%)
Intersection	260 (78.8%)	70 (21.2%)	330 (28.3%)
Traffic control			
Uncontrolled	471 (80.1%)	117 (19.9%)	588 (50.4%)
Controlled	453 (78.4%)	125 (21.6%)	578 (49.6%)
Presence of median			
No	240 (85.1%)	42 (14.9%)	282 (24.2%)
Yes	684 (77.4%)	200 (22.6%)	884 (75.8%)
Road geometry			
Straight and flat	887 (79.8%)	225 (20.2%)	1112 (95.4%)
Others	37 (68.5%)	17 (31.5%)	54 (4.6%)
Road surface			
Brick	7 (87.5%)	1 (12.5%)	8 (0.7%)
Sealed	917 (79.2%)	241 (20.8%)	1158 (99.3%)
Road class			
Highway	298 (82.5%)	63 (17.5%)	361 (31.0%)
Others	626 (77.8%)	179 (22.2%)	805 (69.0%)
Land use proportion within 250 m buffer from crash incidence location			
Residential land use	0.287 (0.18)	0.285 (0.18)	
Commercial land use	0.082 (0.09)	0.081 (0.09)	
Industrial land use	0.021 (0.07)	0.016 (0.06)	

Factors	Level of severity		Total
	Fatal [N (%)/μ (σ)]	Non-fatal [N (%)/μ (σ)]	
Mixed land use	0.115 (0.11)	0.119 (0.12)	
Institutional land use	0.051 (0.11)	0.067 (0.13)	
Restricted land use	0.064 (0.14)	0.053 (0.13)	
Open space land use	0.028 (0.07)	0.033 (0.07)	
Presence of key features within 250 m buffer from crash incidence location			
Presence of educational institute			
No	190 (82.3%)	41 (17.7%)	231 (19.8%)
Yes	734 (78.5%)	201 (21.5%)	935 (80.2%)
Presence of hospital			
No	630 (79.9%)	158 (20.1%)	788 (67.6%)
Yes	294 (77.8%)	84 (22.2%)	378 (32.4%)
Number of bus stop	0.82 (0.55)	0.75 0.58)	

5.2 Results of the Estimated Models

5.2.1 Binary Logistic Regression (BLR)

This study estimated a BLR model to explain the probability of fatal crash occurrence in the study area. **Table 5-2** shows the results of the estimated model, including coefficient (β), standard error (*S. E.*), *p*-value, odds ratio (*OR*), and upper and lower limit of *OR* at 95% confidence interval. There was an absence of multicollinearity among the independent variables, assessed through the *VIF* test (all *VIF* statistics < 1.2). The overall model was found statistically significant at a 99% confidence level ($p < 0.01$). Seven independent variables were found to be statistically significant in the model. Those variables are the time of day, light condition, weather condition, presence of median, road geometry, institutional land use, and number of bus stop. Detail interpretation of the results is provided in **Section 5.3.2**.

Table 5-2: Binary logistic regression model results

Independent variable	Coef. (β)	S. E.	*p*-value	Odd Ratio (*OR*)	95% C.I. for OR		
					Lower	Upper	Difference
Intercept	3.295	0.876	0.000	26.990			
Time of day (ref: day)							
Night	0.332	0.164	0.042	1.394	1.012	1.921	0.909
Light condition (ref: unlit)							
Well-lit	-1.391	0.534	0.009	0.249	0.087	0.708	0.621
Weather condition (ref: adverse)							
Fair	-1.173	0.618	0.058	0.309	0.092	1.039	0.947
Presence of median (ref: absent)							
Present	-0.620	0.189	0.001	0.538	0.372	0.779	0.407
Road geometry (ref: others)							
Straight and flat	0.842	0.317	0.008	2.321	1.248	4.316	3.068
Institutional land use	-1.152	0.593	0.052	0.316	0.099	1.010	0.911
Number of bus stop	0.225	0.131	0.086	1.252	0.968	1.619	0.651
Model statistics Highest VIF value=1.13 χ^2 = 43.362, df = 07, *p*-value = 0.000 Deviance: 1148 Percent deviance explained: 0.036 AIC: 1164							

5.2.2 Geographically Weighted Logistic Regression (GWLR)

This study wanted to estimate a well-fitted and well-explained GWLR model to identify the spatial variation in the magnitude of effects of the independent variables across the study area. An optimal bandwidth selection is essential for estimating a well-fitted and well-estimated GWLR model. However, it is difficult to select an optimal bandwidth as there is an absence of clear guidelines for optimal bandwidth selection. In general, researchers use the *AIC* optimization technique to determine optimal bandwidth while estimating the GWLR model. Therefore, this study estimated a GWLR model with adaptive bisquare kernel function using the *AIC* optimization technique. However, according to Guo, Ma and Zhang [122], *AIC* optimization might not always produce optimal bandwidth. Therefore, this study also decided to develop three other models using three different adaptive bandwidths: 291

(25% of total observations), 583 (50% of total observations), and 875 (75% of total observations). Then, these four models were compared to identify the model with optimal bandwidth. The *OR* statistics of these four GWLR models were summarized and presented in **Table 5-3**. Model fitness parameters of the developed models are shown in **Table 5-4**. Multicollinearity was not an issue for any of the four developed GWLR models since the highest local *VIF* statistic for all the models was less than 2 **(Table 5-4)**.

Bandwidth was found 1,165 in the GWLR model, which was developed using the *AIC* optimization technique. This model is named as GWLR-1165 model in this study. This bandwidth indicated that 1,165 points were included under an adaptive bandwidth to develop each local model. The total number of observations was 1,166 in this study. As almost all the points were considered to develop each of the local models, the developed GWLR model using the *AIC* optimization technique failed to explore a substantial portion of the variation in the intensity of effects of the independent variables. This was confirmed by comparing the difference between 95% *C.I.* for *OR* of the BLR model with the *OR* range of the GWLR-1165 model **(Table 5-2** and **Table 5-3**). Similar to this study, previous studies also showed that large bandwidth failed to explore local variations and estimated results that converged to the global model estimators [122, 123]. On the other hand, model fitness parameters showed that this model had the lowest *AIC* statistics among the four models, indicating comparatively better model fit (**Table 5-4**). However, the lowest percent deviance explained statistics and the highest deviance statistics of this model showed poor model fit compared to the other three models.

Among the four models, the GWLR model with a bandwidth of 291 (GWLR-291) showed the highest variation in the intensity of effects of the independent variables, and the GWLR-1165 showed the lowest (**Table 5-3**). The rest of the two models showed moderate variation. The GWLR model with a bandwidth of 583 (GWLR-583) showed comparatively larger variations than the GWLR model with 875 (GWLR-875). So, it could be said that GWLR models tended to be more global in nature (like the BLR model) with an increase in the bandwidth size. Comparing the *OR* range of the GWLR-291 model with the difference between 95% *C.I.* for *OR* of the BLR model, it could be easily identified that the GWLR-291 model overestimated the variation, which is more likely to be unreasonable (**Table 5-2** and **Table 5-3**). Previous studies also showed that the GWR models with smaller bandwidth sizes might overestimate and overfit the local models [4, 122]. The percent deviance explained and deviance statistics were found the best for this model as this model operated on a much more local scale. However, its *AIC* statistic is relatively higher than other GWLR models indicating poor model fit.

From the above discussion, it is clear that the GWLR-291 and GWLR-1165 were not well-fitted and well-explained models for this study. Now, comparing the *OR* range of the rest two models with the difference between 95% *C.I.* for *OR* of the BLR model, it was found that the GWLR-583 explained the variation of the intensity of effects of the independent variables better than the GWLR-875 (**Table 5-2** and **Table 5-3**). Although the GWLR-875 could explain a portion of the intensity variation, there was still a fair portion of the variation which remained unexplained. In addition, a minimal reduction in the *AIC* statistics was found for the GWLR-875 compared to the GWLR-583, indicating a very marginal improvement for the GWLR-875 model (**Table 5-4)**. However, the percent deviance explained and deviance statistics substantially improved in the GWLR-583 model than the GWLR-875 model. Therefore, it could be concluded that the GWLR-583 was a comparatively better performed and better-fitted model among the four developed GWLR models. In the latter part of the chapter, the results of the GWLR-583 model have been interpreted and explained. The spatial distribution of the *OR* statistics of the model's independent variables is presented in **Figure 5-2**. Details of the results are discussed in the following section (**Section 5.3.2**).

Table 5-3: Summary statistics of odds ratio (*OR*) estimated through the GWLR

	Minimum				**Median**				**Maximum**				**Range**			
Bandwidth	**291**	**583**	**875**	**1165**	**291**	**583**	**875**	**1165**	**291**	**583**	**875**	**1165**	**291**	**583**	**875**	**1165**
Intercept	0.53	5.87	9.72	14.72	587.73	23.13	19.44	20.20	797837	240.49	84.17	36.22	797836	234.62	74.45	21.50
Time of day	0.75	0.91	1.12	1.20	1.26	1.31	1.25	1.37	3.12	2.37	1.78	1.56	2.37	1.46	0.66	0.36
Light condition	0.00	0.09	0.14	0.18	0.23	0.19	0.23	0.26	0.98	0.46	0.32	0.29	0.98	0.37	0.18	0.11
Weather condition	0.00	0.02	0.21	0.28	0.08	0.37	0.36	0.34	5.08	0.89	0.50	0.43	5.08	0.87	0.29	0.15
Presence of median	0.27	0.36	0.40	0.48	0.61	0.60	0.61	0.61	1.10	0.78	0.64	0.63	0.83	0.42	0.24	0.15
Road geometry	0.14	1.37	1.61	2.27	2.25	2.56	2.54	2.55	13.68	8.44	4.44	3.20	13.54	7.07	2.83	0.93
Institutional land use	0.00	0.12	0.18	0.21	0.35	0.26	0.27	0.32	13017302	3.68	0.57	0.43	13017302	3.56	0.39	0.22
Number of bus stop	0.49	0.83	1.14	1.16	1.27	1.21	1.30	1.25	2.68	1.59	1.34	1.32	2.19	0.76	0.20	0.16

Table 5-4: Model fitness parameter of the GWLR models

Fitness parameter	**GWLR-291**	**GWLR-583**	**GWLR-875**	**GWLR-1166**
Deviance	1081	1120	1137	1144
Percent deviance explained	0.092	0.06	0.045	0.039
AIC	1191	1176	1173	1168
Highest VIF statistics	1.26	1.18	1.16	1.14

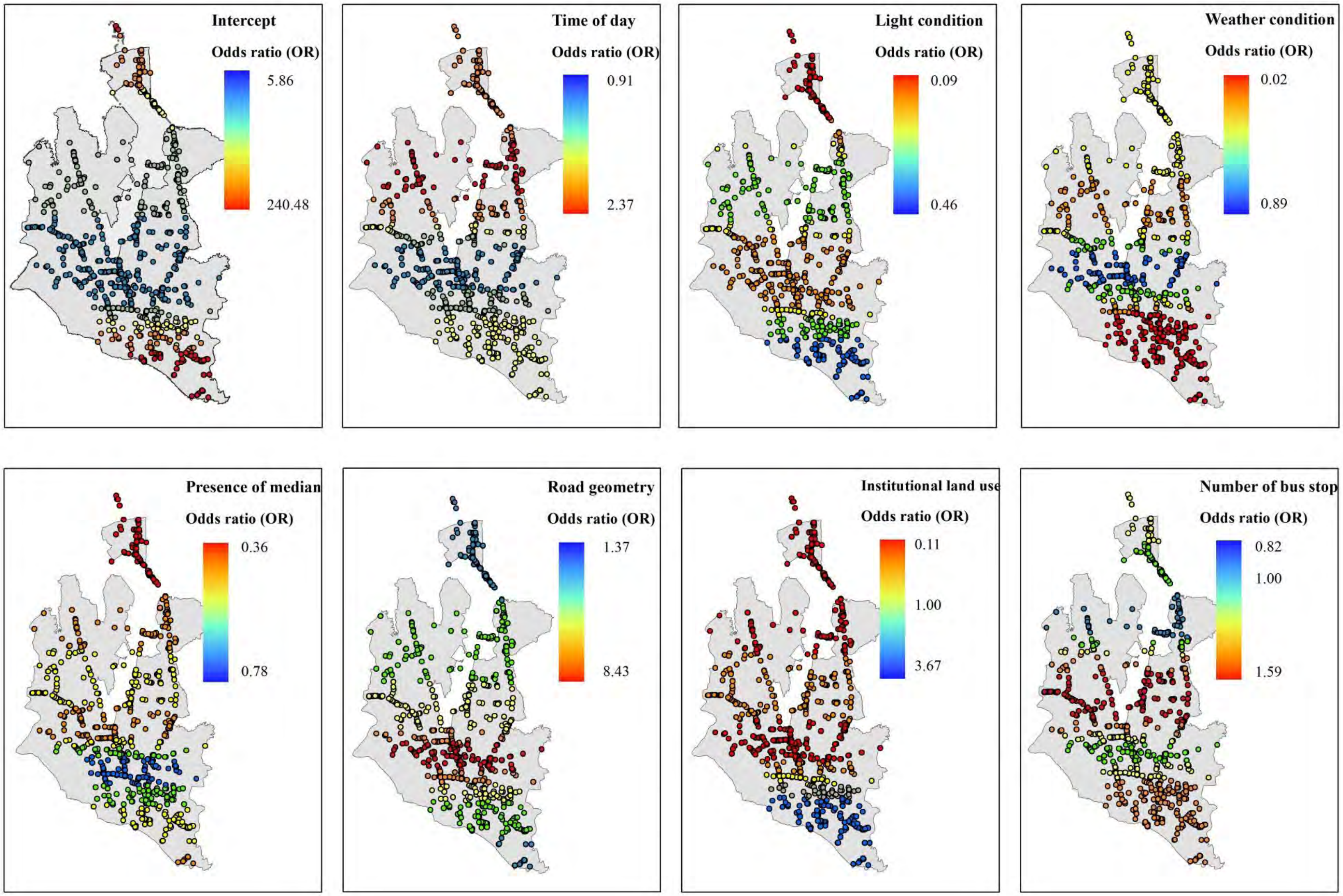

Figure 5-2: Spatial distribution of odds ratio (*OR*) of the GWLR-583 model

5.3 Discussion

5.3.1 Model Estimation

Comparing both BLR and GWLR-583 model, this study found that the deviance value was reduced from 1,148 (for BLR model) to 1,120 (for GWLR-583 model), and the percent deviance explained value was increased from 0.036 (for BLR model) to 0.6 (for GWLR-583 model). A large improvement in the deviance value indicated that local models fitted well while explaining the spatial data compared to the BLR model. In addition, the percent deviance explained value increased by about 0.024, indicating that the GWLR-583 model also improved the explaining power of pedestrian crash severity compared to the BLR model. Therefore, it can be said that both models have the capability to model pedestrian crash severity, but the GWLR-583 model was more efficient and able to identify spatial variation in the relationships between crash severity and independent variables.

Although these two model fitness parameters showed a significant improvement in the GWLR-583 model compared to the BLR model, the *AIC* statistics indicated the opposite result. The *AIC* statistics increased in the GWLR-583, indicating deterioration in the model performance. It is important to note that the GWR techniques are primarily used to explore spatially heterogeneous relationships between the dependent and independent variables. They are not usually used to improve performance compared to the global models [79, 115]. Finally, it can be concluded that the GWLR-583 model was superior to the BLR model in explaining the spatial relationships between pedestrian crash severity and independent variables, including exploring spatial variation in the relationships, which was the main purpose of using the GWLR model in this study.

5.3.2 Model Findings and Implications for Planning

5.3.2.1 Natural environment characteristics

The results of the BLR model identified the significant independent variables, and the GWLR model showed the spatial variation of their intensity. Among the natural environment characteristics, time of the day, light condition, and weather condition were found to be significant. The likelihood of fatal crash occurrence increased 1.39 times if the crash occurred during the night compared to the day (**Table 5-2**). This result was found to be consistent with previous studies [40, 50]. In general, traffic volume is comparatively lower, vehicle operating speed is much higher, and a larger volume of heavier vehicles operates during the night period compared to the day period in Dhaka. Also, visibility is poor during the night than day. Therefore, the fatal crash risk might increase during the night period. Time of day had the highest variation in the intensity of effect among the natural environment characteristics related factors across the study area (Range: 0.91–2.37) (**Table 5-3**). **Figure 5-2** shows that this variable had much more impact on the northern side of the study area and was less impactful in the central part. The presence of an international airport and two national highways, which connect Dhaka with other parts of the country, might keep the northern area busy with pedestrians and heavy vehicles at night and could be the reason behind the results.

On the other hand, the probability of a fatal crash decreased 0.249 times if the collision occurred at a well-lit place than a dark place. Fair weather conditions also reduced the likelihood of fatal crashes 0.3 times compared to adverse weather conditions (**Table 5-2**). Previous studies also showed similar results [41, 49, 50]. However, Kim, Ulfarsson, Shankar and Kim [43] reported the opposite result in the case of weather condition. The visibility of pedestrians and drivers is significantly reduced at unlit places and during adverse weather conditions (e.g., rainy, foggy), and consequently, leading to an increase in the chance of fatal crashes [6, 50]. Other reasons that might increase fatal crash probability could be the malfunction of the vehicle, slippery roads, waterlogging, huge traffic congestion, and risky driving behavior during the adverse weather, especially rainy weather [6]. The light condition had comparatively lower intensity variation (Range: 0.09–0.46), and the weather condition had a comparatively higher variation in intensity (Range: 0.02–0.89) across the study area (**Table 5-3**). The impact of light conditions was significantly higher in the northern area and lesser in the southern part of the study area. The reason could be the presence of very wide roads in the northern areas, where street lights or lights from surrounding structures might fail to illuminate the wide road properly. Besides, higher intensity of impact was found in the southern part of the study area in case of weather conditions (**Figure 5-2**). The southern part of the city is much older than the northern part. Therefore, the northern part of the city was developed in a more planned way with better infrastructures and drainage facilities. Whereas, southern part was developed spontaneously without providing proper infrastructures and draining facilities. Therefore, impact of weather condition might be found much higher in the southern part.

To minimize the effects of natural environment factors that increase pedestrian crash severity, a proper street lighting system should be installed and operated to illuminate the whole road network, especially in footpath and crossing locations. In addition, problems of the street lighting system (e.g., absence of lights, faulty lights, difficulty in maintenance and monitoring, load shedding, and so on) need to be solved. Finally, education and training programs for drivers and pedestrians need to be taken to reduce pedestrian crashes and their severity during unlit and adverse weather conditions.

5.3.2.2 Built environment characteristics

5.3.2.2.1 Roadway characteristics

Among the roadway characteristics at the crash location, presence of median and road geometry were significant. The likelihood of a fatal crash decreased 0.53 times if the crash occurred on a road with a median compared to the road without median **(Table 5-2)**. This result was found consistent with Zafri, Prithul, Baral and Rahman [6]. However, the opposite result was also found in the previous literature [40, 43]. According to Zafri, Prithul, Baral and Rahman [6], without a median, discipline in the vehicle flow on the road is hampered, and conflicts increase; additionally, pedestrians find it difficult to cross wide roads where medians are not present. Therefore, the fatal crash risk increased on roads having no median. In addition, the probability of fatal crashes increased 2.3 times on straight and flat roads compared to curved and sloppy roads (**Table 5-2**). The opposite result was reported in the study of Amoh-Gyimah, Aidoo, Akaateba and Appiah [50]. Straight and flat roads allow vehicles to operate at high speed. Therefore, the high speed of the vehicles led to increase fatal crash probability [6]. The presence of median had a higher impact in the northern part and lower impact in the central part of the study area; however, this result was found opposite for road geometry (**Figure 5-2**).

Medians need to be provided on wide roads as per design standards to minimize the effects of roadway factors that increase the probability of fatal crashes. The provision of a narrow median might not facilitate pedestrians to cross safely. Median should work as a refuge island so that the pedestrians can wait on it while crossing. Also, a proper vehicular speed control mechanism needs to be installed on the roadways, especially on straight and flat roads. The speed limit needs to be assigned on each road and should be shown through proper traffic signage and marking. The traffic control devices (e.g., traffic signal, marking, stop sign, crosswalk) need to be installed to control the speed of the vehicle, especially at the locations where pedestrians cross regularly. In addition, the speed restriction rule should be strictly enforced so that no vehicle exceeds the limit.

5.3.2.2.2 Land use characteristics

Institutional land use was the only variable that was found to be significant among the land use variables. The likelihood of fatal crashes decreased if the institutional land use proportion increased surrounding the pedestrian crash location (**Table 5-2**). The reason could be that pedestrian facilities, speed control mechanisms, and traffic management surrounding institutional land use were comparatively better than other areas, and consequently, reduced fatal crash risk. Institutional land use had a larger variation in the magnitude of effect across the study area (Range: 0.12–3.68) (**Table 5-3**). This variable had a higher impact in the central and northern parts of the study area (**Figure 5-2**). On the other hand, the impact of this variable was found the opposite in the southern part of the study area. In that part, with an increase in the institutional land use proportion, the likelihood of fatal crashes increased. The reason behind the result could be that the northern and central part have upscale institutions than the southern part, where better road infrastructure and pedestrian facilities are available. It is also mentionable that a negligible amount of institutional land use is present in the southern part of the study area. Further studies should be conducted on the pedestrian facilities in institutional areas and replicate the good practices in the other areas.

5.3.2.2.3 Presence of key features

The number of bus stops was also found to be a significant variable. A higher number of bus stops surrounding pedestrian crash locations tended to increase the fatal crash occurrence probability (**Table 5-2**). This result was not found consistent with previous studies [20, 49]. The higher number of bus stops means a higher number of conflicts between heavy vehicles (bus) and pedestrians at the time of loading and unloading passengers since bus stops in the study area were not well-structured and well-marked, as well as there is a lack of discipline at bus stops [118]. Also, there is a tendency for embarking on and disembarking from a running bus in the study area as the buses often do not completely come to a halt at bus stops. These might be the reasons behind the higher probability of fatal crash occurrences. A small variation was found in the intensity of the impact of this variable throughout the study area (Range: 0.83–1.34) (**Table 5-3**). This variable had higher intensity of impact in the central and southern part of the study area. The presence of three largest bus terminals of the city in those parts (Gabtoli, Mohakhali, and Sayedabad) could be the reason behind this result. Implementation of proper design, including safety elements in the design of these terminals and bus stops, and ensuring road users' discipline at these locations could ensure pedestrian safety.

5.3.3 GWLR model prediction

The GWLR-583 model estimated a map of the predicted probability of fatal crash occurrence across the study area (**Figure 5-3**). The map shows that the northern part of the study area had the highest likelihood of fatal crash occurrence. Multiple factors, such as time of day, light condition, presence of median, and institutional land use, had a higher magnitude of impacts in the northern part of the city, which might make this part more fatal crash-prone. In contrast, the central and southern parts of the study area had a moderate probability of fatal crash occurrence.

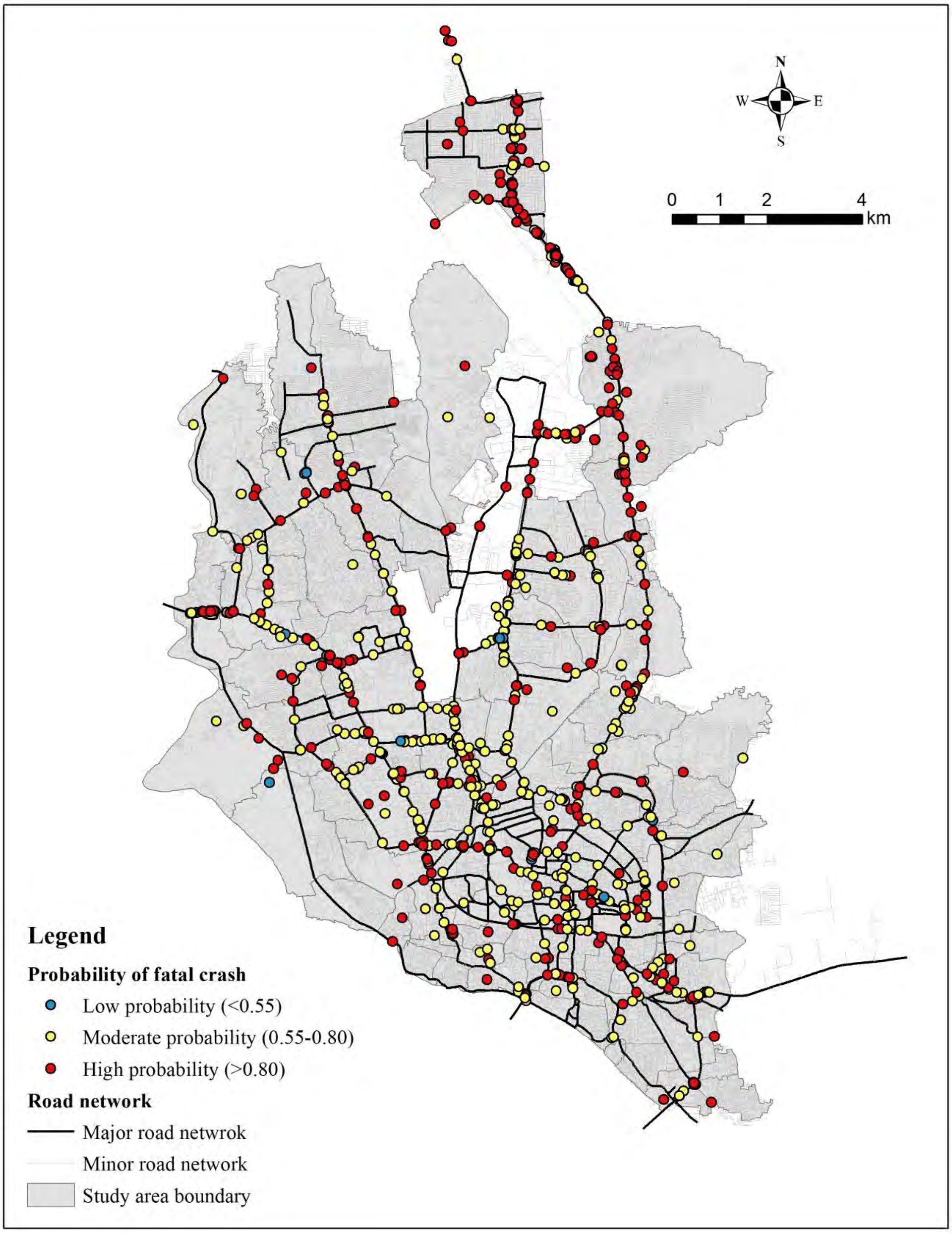

Figure 5-3: Probability of fatal crash occurrence estimated through GWLR-583

CHAPTER 6: CASE ANALYSIS: LINKAGE BETWEEN MACROSCOPIC AND MICROSCOPIC ANALYSIS

In this chapter, first, the relationship between pedestrian crash occurrences and crash severity was explored. Then, three wards having the highest crash density were selected, and a detail observational analysis was conducted to explore the relationship between crash occurrences and severity with built environment factors.

6.1 Relationship between Pedestrian Crash Occurrences and Crash Severity

To assess the relationship between pedestrian crash occurrences and crash severity, this study divided all the wards into five types based on pedestrian crash density: very low, low, moderate, high, and very high. Distribution of fatal and non-fatal crashes among the five types of wards was estimated and presented in **Table 6-1**. Findings from the table show that 38% of the fatal crashes occurred in very high crash density wards and 6.1% of them occurred in very low density wards. In the case of non-fatal crashes, 5.1% and 39% of the non-fatal crashes occurred in very low and very high crash density wards, respectively. From the table, it is clear that distribution of fatal and non-fatal crashes in the five types of wards was almost equal. The result of the Chi-Square Test of Independence was found insignificant ($p > 0.1$), indicating there was no association between pedestrian crash severity and crash density. More specifically, crash severity did not depend on how many crashes took place in a location.

Table 6-1: Relationship between macroscopic level pedestrian crash density (crash/ha) and microscopic level crash severity

Crash severity	Crash density in a ward				
	Very low (0-0.02)	Low (0.02-0.05)	Moderate (0.05-0.1)	High (0.1-0.17)	Very high (0.17-0.45)
Fatal	6.1%	9.9%	25.7%	20.3%	38.0%
Non-fatal	5.1%	9.2%	26.2%	20.5%	39.0%
Chi-Square Test of Independence: $\chi^2 = 0.352$, $df = 4$, p-value = 0.9861					

6.2 Case Analysis: High Pedestrian Crash Density Wards

In the macroscopic and microscopic analysis, this study considered the proportion of different land uses in wards and within 250m buffer from each crash location, respectively. However, it was not possible to answer the question: what was the impact of the immediate/closest land use/ building use on pedestrian crash occurrences and crash severity from the previous analyses. Therefore, for detail crash analysis, this study selected three wards with very high crash density and analyzed crash pattern in those wards. Those three wards are Dhanmondi, Saidabad, and Ramna. In the following sub-sections, this study presents the findings of the case-specific analysis.

6.2.1 Case 1: Dhanmondi

In Dhanmondi, around 65 crashes occurred from 2010 to 2015. Among them, 49 crashes had a fatal outcome. Almost all the crashes occurred on the major roads of Dhaka: Mirpur road, Satmasjid road, and Manik Mia Avenue (**Figure 6-1**). These roads can be characterized by substantial motorized and non-motorized traffic volume as well as wide roads with heavy vehicles. However, very few crashes also occurred on the local roads. In addition, the crash frequency was found higher near major intersections. These two results are consistent with the findings of the macroscopic crash occurrences analysis, which showed that crashes occurred more in the wards having higher primary road density as well as major intersection density.

Though the ward is used predominantly for residential purposes, very few crashes occurred in front of the residential buildings. Crashes occurred mostly in front of commercial buildings. A sizable number of crashes also occurred in front of the buildings, which were used for mixed and educational purpose. The reason could be that residential buildings have low activity as well as attract few people throughout the day. On the other hand, commercial, mixed, and educational buildings can attract a huge number of people as well as vehicles throughout the day. In addition, people are usually boarding and alighting from the public transport near these types of buildings. Also, they might need to cross the wide roads to access these types of buildings. In short, a large number of complex activities occurred around commercial, mixed, and educational buildings, which increased crash frequency in front of them. In macroscopic pedestrian crash occurrences analysis, this study found that pedestrian crash density was higher in wards having higher mixed land use density, which is consistent with this finding.

Apart from this, it is worth to mention that fatal and non-fatal crashes were found to occur in the same places. So, it is difficult to find any identical pattern in the distribution of fatal and non-fatal crash occurrences.

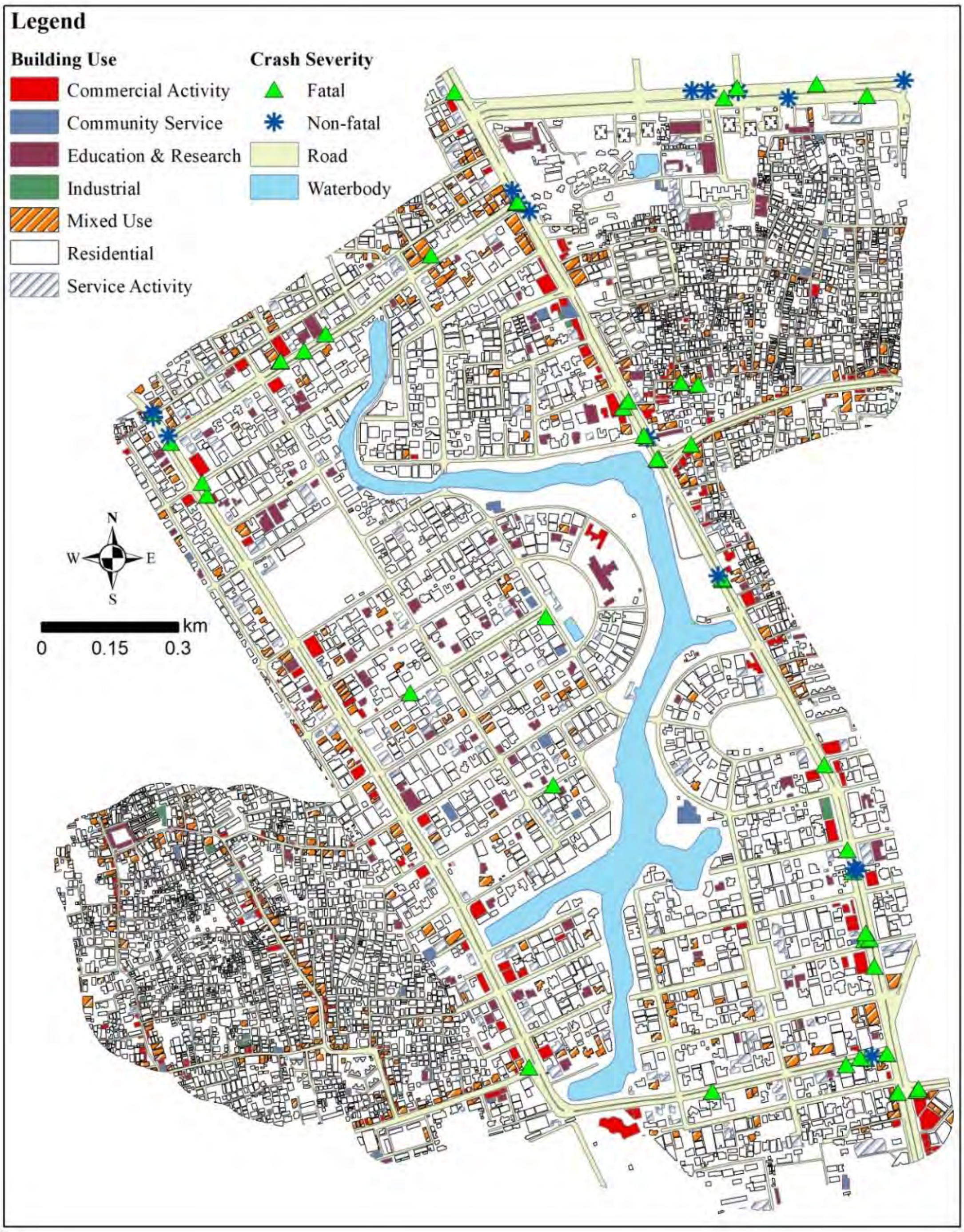

Figure 6-1: Crash distribution and building use in Dhanmondi

6.2.2 Case 2: Saidabad

Around 26 crashes occurred in Saidabad from 2010 to 2015. Among them, 20 crashes had a fatal outcome. Like Dhanmondi, most of the crashes occurred on major roads (Dhaka-Sylhet Highway), near major intersections, as well as in front of commercial, mixed, and educational buildings (**Figure 6-2**). Apart from this, crashes occurred mostly around the Saidabad Bus Terminal. Here, it is difficult to find any identical pattern in the distribution of fatal and non-fatal crashes like Dhanmondi.

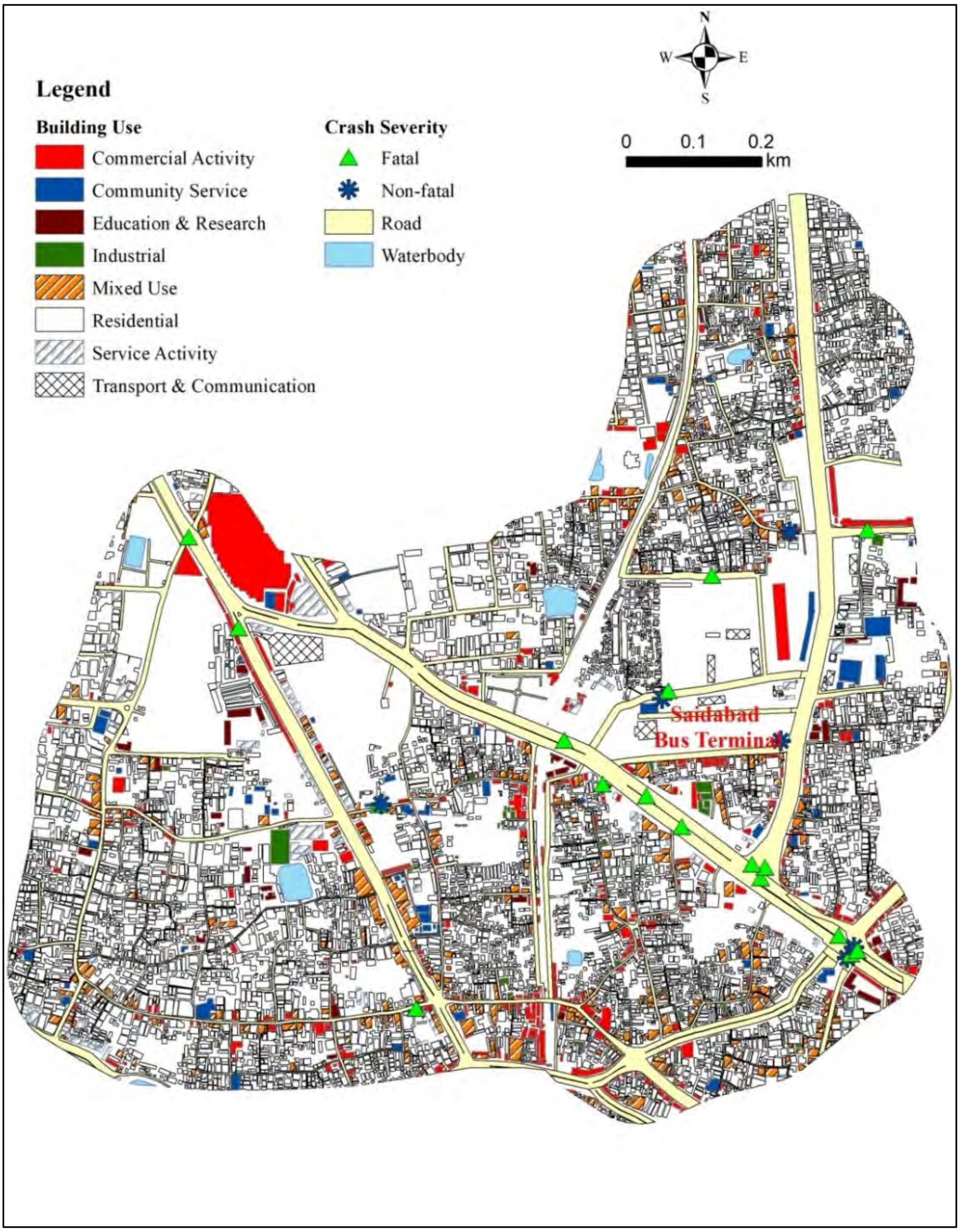

Figure 6-2: Crash distribution and building use in Saidabad

6.2.3 Case 3: Ramna

In Ramna, around 56 crashes occurred from 2010 to 2015. Among them, 41 crashes had a fatal outcome. Like Dhanmondi and Saidabad, most of the crashes occurred in major roads (Kakrail Road, Moghbazar Road, Outer Circular Road, Kazi Nazrul

Islam Avenue, and Baily Road), near major intersections, as well as in front of commercial, mixed, and educational building use (**Figure 6-3**). It is worthy to mention that Ramna Park had increased crash frequency in front of Kakrail mosque, which was found consistent with the result of the macroscopic analysis of this study. Kakrail mosque is a very vibrant large mosque of Bangladesh, which attracts a large number of people throughout the day. So, the place becomes busy with many activities due to the presence of Ramna Park and Kakrail mosque, and consequently, crashes occurred more there. In addition, it is difficult to find any identical pattern in the distribution of fatal and non-fatal crashes like Dhanmondi and Saidabad.

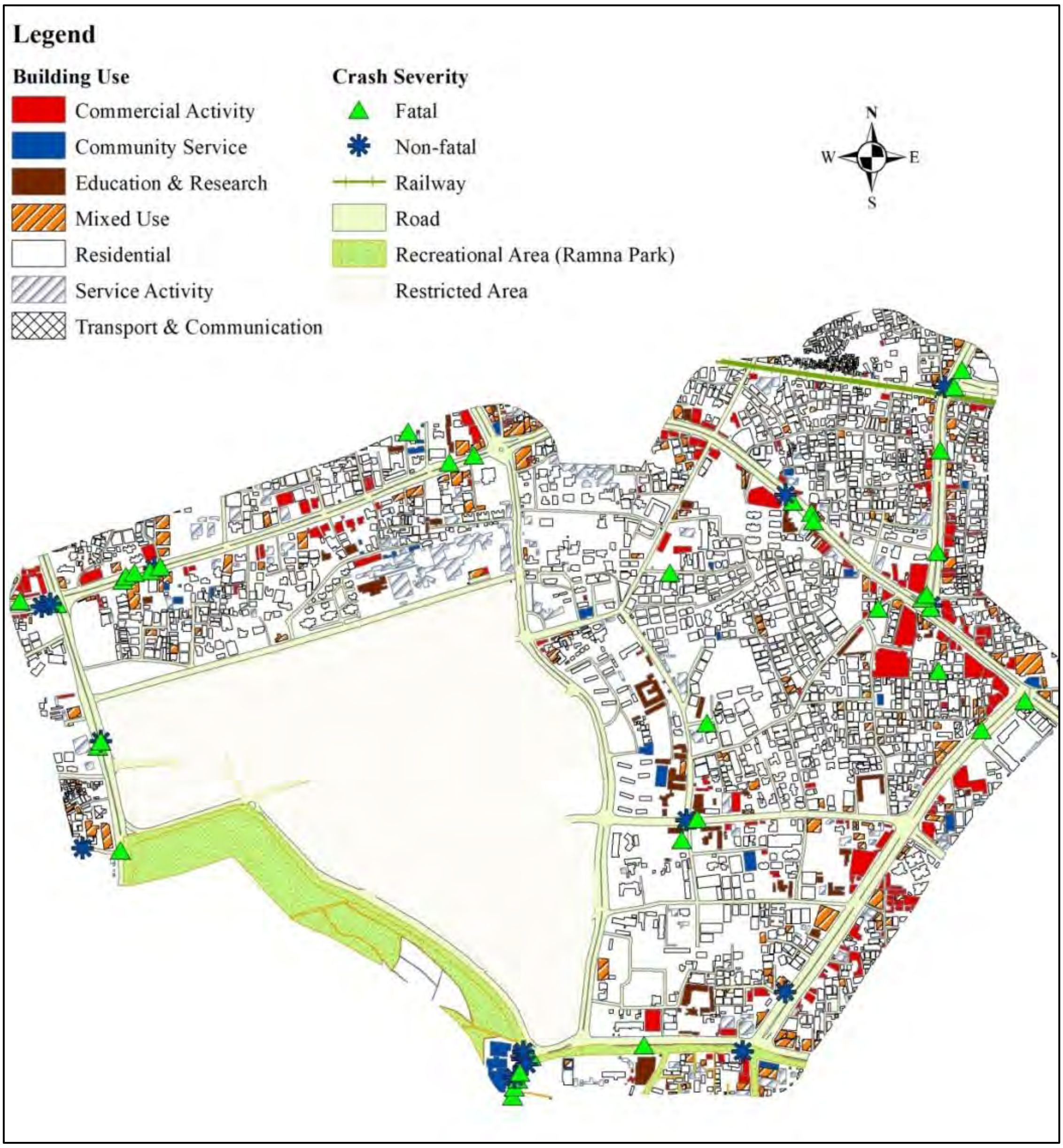

Figure 6-3: Crash distribution and building use in Saidabad

6.2.4 Summary from Case Analysis and Implication for Planning

From the case-specific analysis, it is worthy to mention that crashes occurred more on major roads as well as major intersections. In addition, crashes also occurred more near buildings/ spaces used for commercial, mixed, educational, and recreational purposes. From the macroscopic crash occurrences analysis, this study found that the crash density was higher in wards with higher densities of major road and intersection as well as mixed and recreational land use. These findings were found consistent with case-specific analysis. So, the recommendations suggested in the macroscopic analysis for these factors are also valid and applicable here (See **Section 4.3.2**). However, one of the interesting and unique findings of the case analysis is that crashes occurred more in front of commercial and educational buildings as well as a large vibrant mosque. Pedestrian safety needs to be improved adjacent to commercial area, educational institute, and mosque through different types of measures. Attention should be paid to minimize potential pedestrian-vehicle conflicts by separating pedestrians from vehicular movement through safe walkways and crossings. Traffic management measures also need to be put in place to control the vehicular speed. Land use measures like providing pedestrian precincts in suitable commercial hubs could be useful. These measures could be complemented by safety awareness-raising campaigns.

CHAPTER 7: CONCLUSION

This study aimed to explore the effects of the built environment on the pedestrian crash occurrence and pedestrian crash severity through non-spatial and spatial regression models in the context of Dhaka, Bangladesh. Findings of the pedestrian crash occurrences analysis suggested that six significant built environment factors affected pedestrian crash density in the study area. These factors are employed person density, mixed land use density, recreational land use density, primary road density, major intersection density, and non-motorized modes share. Pedestrian crash density had a positive relationship with all the variables except non-motorized modes share. In addition to that, spatial relationships between pedestrian crash density with primary road density and major intersection density were found local according to the MGWR model. An important contribution of this study was that it provides a methodological framework for using spatial regression methods to explore the effects of the built environment on pedestrian crash occurrence incorporating spatial autocorrelation and exploring spatial non-stationarity relationships considering various spatial scales. This study suggested that the MGWR method has a great potential for macroscopic crash modeling to estimate more accurate results than other traditional models. This technique also helps to explore local relationships at different spatial scales.

On the other hand, results of the pedestrian crash severity analysis found that the probability of fatal crash occurrence increased at night period, unlit place, and during adverse weather. The likelihood of fatal crashes was reduced on the roads where median was available, and a higher proportion of institutional land use was found surrounding the road. Also, fatal crashes tended to occur more at straight and flat roads and roads where a higher number of bus stops were presented. This study explored spatial variation in the intensity of the relationships between pedestrian crash severity with significant natural and built environment-related factors using the GWLR modeling technique. Higher intensity variation was found for road geometry and institutional land use variables. On the other hand, lower intensity variation was found for light condition and presence of median factors. The results of this study identified that the GWLR model had a better explaining capability than the BLR model.

To bridge between macroscopic and microscopic analysis, this study selected three high crash density wards and analyzed crash and built environment pattern to find more comprehensive results. The findings of this analysis were found consistent with the findings of the macroscopic analysis. However, additional findings were that crashes occurred more around commercial and educational buildings as well as in front of large mosques.

Based on the findings of this study, this study suggested recommendations that would help the urban and transport planners to improve pedestrian safety in developing countries. A summary of those recommendations are presented below.

- Implementation of an integrated multimodal transport plan and proper design of bus stops and bus terminals could ensure pedestrian safety by ensuring safe transfer from one mode to another.
- Retrofitting the existing primary roads and surrounding areas, taking a complete street scheme, providing pedestrian facilities according to the standard, and providing median on the major roads could decrease the vulnerability of the pedestrians on the major roads.
- In major intersections, it is recommended to provide proper pedestrian crossing facilities considering their needs, install traffic control devices (e.g., traffic signals, marking, stop signs, crosswalks), and prioritize pedestrians to ensure safe crossing opportunities.
- Vehicle operating speed needs to be controlled on each major road, especially in mixed, commercial, recreational, and educational areas. Speed limit should be shown through proper traffic signage and marking. In addition, the speed restriction rule should be strictly enforced so that no vehicle exceeds the limit.
- To increase non-motorized traffic volume, especially in mixed use areas, it is recommended to restructure the urban built environment by implementing appropriate planning strategies, such as TOD, smart growth, and compact development, and adopting complementary traffic management measures.

Travel demand management related strategies should be implemented to reduce vehicular traffic volume. Pedestrian precincts could be encouraged in highly dense commercial areas.

- A proper street lighting system must be installed and operated to minimize the effect of unlit condition and adverse weather condition.
- Awareness-raising programs for both pedestrians and drivers should be taken to ensure pedestrian safety.

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APPENDIX

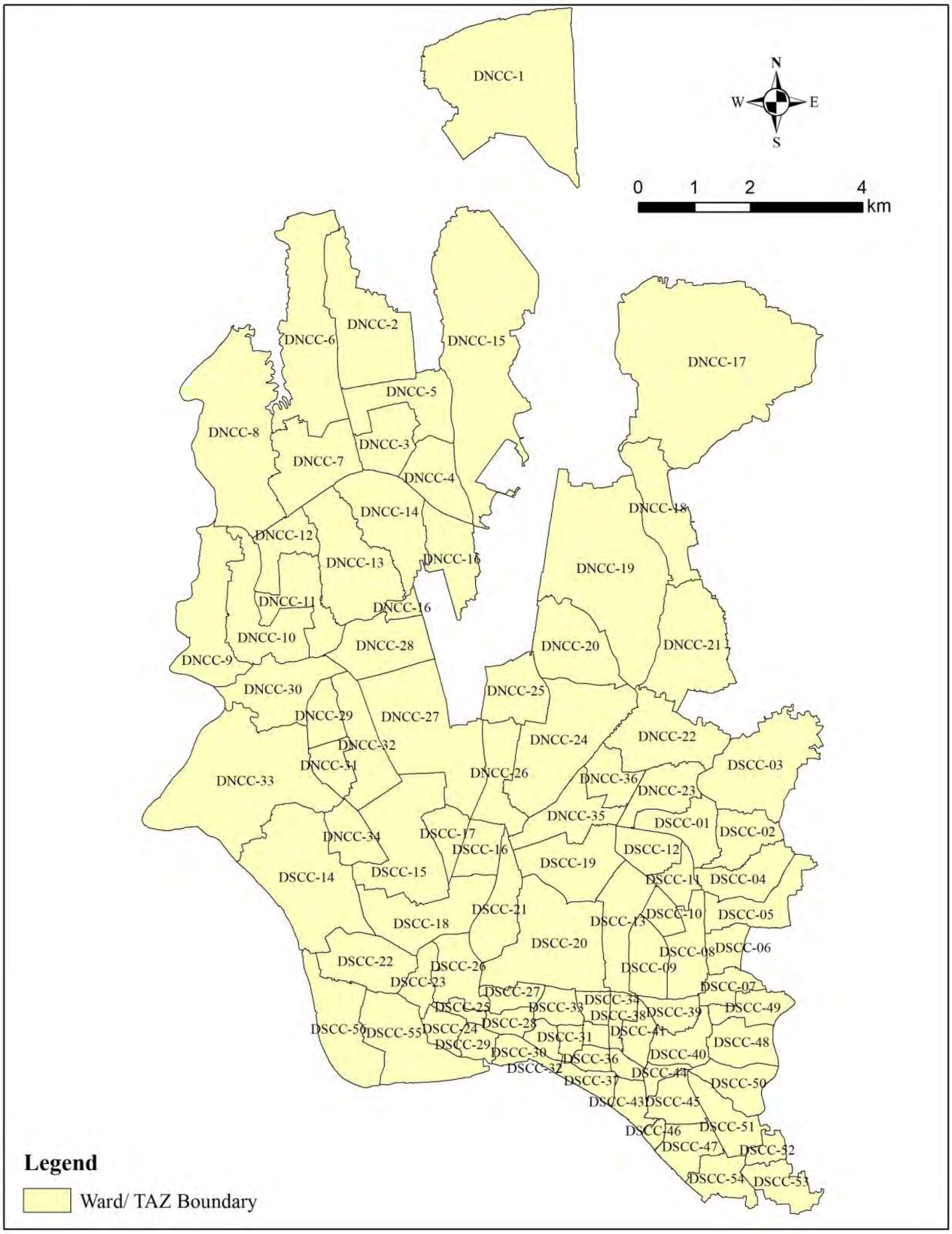

Figure A1: Map of the study area