School of Design and the Built Environment

Development of Geospatial Models for Multi-Criteria Decision Making in Traffic Environmental Impacts of Heavy Vehicle Freight Transportation

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Declaration

To the best of my knowledge and belief this thesis contains no materials previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

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Abstract

Heavy vehicle freight transportation is one of the primary contributors to socio-economic development, but it also has great influence on the traffic environment. An accurate and comprehensive understanding of the influence of heavy vehicle freight transportation on traffic environment is critical for informed decision making concerning traffic and road systems management and for satisfying users' requirements. The accurate analysis and efficient management of traffic environment can bring great benefits to communities for their easy access to roads and facilities, to industries for the efficiency improvement and cost reduction, and to authorities for smart management of road assets. To quantify the impacts of heavy vehicle freight transportation, this research develops a series of geospatial models for both geographically global and local assessment of the impacts.

In this research, to explain the methodology, heavy vehicles and their traffic environmental impacts are analysed for the road network across the Wheatbelt in Western Australia (WA), Australia. The Wheatbelt is a major grain and other agricultural production region in Australia. It links the Perth Metropolitan region, the capital city of WA, with mining and agricultural production regions. Heavy vehicles are the predominant transportation tool of mining and agricultural equipment and products. The research consists of the following four stages.

First, road infrastructure performance and factors that can affect the pavement performance are investigated from the geographical information systems (GIS) perspective. To understand the factors associated with the road infrastructure performance, previous research and critical methods about the burden of road maintenance from heavy vehicles, and the comprehensive impacts of multi-source factors on road infrastructure performance are reviewed. Meanwhile, to understand the advantages and potential of current indicators and methods for describing road infrastructure performance, geospatial decision making approaches for road infrastructure management are reviewed. In addition, BIM-GIS integration is an emerging platform that merges advantages of BIM and GIS. It is a rapid developing and innovative trend for both academic research and industries in construction field. In order to better satisfy users' requirements in practical road and vehicle management,

BIM-GIS integration is reviewed and analysed from the aspect of spatio-temporal statistics.

Next, to assess heavy vehicle impacts on the burden of road maintenance, two segment-based spatial prediction models, segment-based ordinary kriging (SOK) and segment-based regression kriging (SRK), are proposed for the spatial prediction of traffic volumes and masses of different types of vehicles. The segment-based spatial prediction models can provide new insights into the spatial characteristics and spatial homogeneity of a road segment during prediction. An R “SK” package is developed for performing the segment-based spatial prediction models. Results indicate that they can more accurately predict traffic conditions compared with traditional methods that deal with point-based observations. The methods are utilized in estimating the burden of road maintenance at road segment level across the road network.

Third, the comprehensive impacts of vehicles, climate, properties of road and socioeconomic conditions on pavement infrastructure performance are investigated using segment-based spatial stratified heterogeneity analysis. In addition to the vehicles that are a primary factor of road conditions discussed above, various other variables also have significant influence on the roads. Meanwhile, their impacts vary greatly on different roads. The segment-based spatial stratified heterogeneity analysis can provide both the impacts of single variables and their interactions. An R “GD” package is developed for applying this approach. The approach in this study provides new ideas for spatial analysis for segmented geographical data and can objectively estimate the contributions of explanatory variables on pavement performance.

Finally, to more comprehensively describe the overall performance of road infrastructure and to select a more accurate performance indicator, this study proposes a model-driven fuzzy spatial multi-criteria decision making (MFSD) approach for comparing different monitoring indicators and computing an overall indicator. The MFSD method can both generate an indicator and support decision making by integrating data-driven model-based decision making, fuzzy set theory, GIS and multi-criteria decision making (MCDM). Results show that MFSD-based indicators can more accurately describe the spatial distribution of road maintenance burden compared with monitored indicators. The outcomes are applied in flexible multi-criteria decision making for road maintenance and management.

This study develops a series of new geospatial methods, and brings new theories and technologies together, for comprehensive investigation of road infrastructure performance and the factors of pavement performance. Using the developed new methods, this thesis provides new findings of road infrastructure performance from a geospatial perspective. In addition to the findings and outcomes, academic and industrial contributions are also summarized and presented in this research. From the academic perspective, this thesis enriches the types of spatial data, presents new knowledge to the theories and methods of road and vehicle research, and provides proper solutions to deep understand the data and the scientific problems. From the practical perspective, with the new methods, data-driven outcomes, tools and software, this study can support more accurate, geographically local and flexible decision making, and benefit local communities, traffic and road authorities and industries.

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Related Publications

Song, Y., Wang, X., Wright, G., Thatcher, D., Wu, P. and Felix, P., 2019. Traffic volume prediction with segment-based regression kriging and its implementation in assessing the impact of heavy vehicles. *IEEE Transactions on Intelligent Transportation Systems,* 20(1): 232-243.

Song, Y., Wang, X., Tan, Y., Wu, P., Sutrisna, M., Cheng, J.C.P. and Hampson, K., 2017. Trends and Opportunities of BIM-GIS Integration in the Architecture, Engineering and Construction Industry: A Review from a Spatio-Temporal Statistical Perspective. *ISPRS International Journal of Geo-Information* 6, no. 12: 397.

Song, Y., Wright, G., Wu, P., Thatcher, D., McHugh, T., Li, Q., Li, S.J. and Wang, X., 2018. Segment-Based Spatial Analysis for Assessing Road Infrastructure Performance Using Monitoring Observations and Remote Sensing Data. *Remote Sensing*, 10(11): 1696.

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Chapter 1 Introduction

1.1 Background

The road network is the predominant transportation infrastructure, and road freight transportation is essential in socio-economic development for all nations. It is estimated that 89% of the variations in freight transportation are associated with economic conditions (Bennathan, Fraser, and Thompson 1992). However, continuously increased freight volumes have caused a series of challenges for local communities and road authorities. One of the primary impacts of road freight transportation is the severe damage to road surfaces and rapidly aging roads compared with maintenance plans. A direct result of such impacts is dramatically increased road maintenance costs. The impacts of road freight transportation also can lead to uncomfortable and unsafe driving, low quality of living environment for local communities and inaccessibility to industrial facilities for industries when they use the roads.

In recent years, the quantification of impacts of road freight transportation has attracted researchers' attention. A growing amount of data can be monitored through various sensors by road authorities and freight transportation industries to estimate the total masses of vehicles and road conditions. These data have been widely applied in road and vehicle management, but more importantly, geographically local and flexible analysis is still critically required for the effective and efficient management. To achieve these objectives, a series of problems about theories and methods have to be solved.

First, it is increasingly critical to investigate road infrastructure performance and explore the factors from the geographical information systems (GIS) perspective. Road performance and factors data are greatly varied across road network. GIS has strengths in visualising the geospatial data with multiple layers, and supports accurate and geographically local analysis of the associations between road performance and factors. Thus, GIS provides diverse theoretical and methodological basis for the geospatial analysis of road and vehicle issues. In addition, the integration of building information modelling (BIM) and GIS provides great potential of spatio-temporal statistical analysis of both road and vehicle data in this research and issues in the broad architecture, engineering and construction industry. BIM supports abundant semantic and geometric information of construction components during the whole life cycle of buildings and cities. GIS contains both theories and techniques of visualisation and analysis of geographical and spatial information. BIM-GIS integration will merge the new geospatial models that have been applied in spatial prediction, factor exploration and decision making related to road infrastructure management.

From the GIS perspective, the road and vehicle spatial data that are linearly distributed along roads and across road network are different from the traditional GIS data sampled by points or areas. Thus, line segment-based spatial data of road and vehicle attributes should be defined to more accurately describe traffic conditions and road infrastructure performance. The impacts of freight transportation on roads across the whole road network are generally predicted based on data at monitored points and parts of road segments. The spatial data of roads and vehicles are characterised in the spatial heterogeneity along road segments, which is totally different from the traditional point-based spatial data. Thus, line segment based spatial data needs to be properly defined and the corresponding prediction methods are required for more accurate estimation of traffic conditions and impacts of freight transportation on roads.

Meanwhile, influence of heavy vehicle freight transportation on road infrastructure performance need to be highlighted. Heavy vehicles are used as the predominant tool for road freight delivery. The total number of heavy vehicles reached 4.14 million globally in 2017, which accounted for 4.26% of all vehicles in use (International Organization of Motor Vehicle Manufacturers 2018). Even though the heavy vehicles are much fewer than light vehicles, heavy vehicle freight transportation is the primary type of freight delivery. For instance, in Europe, the percentage of heavy vehicles is 2.15% of all vehicles, but they support 75.3% of the freight transport including roads, railways and waterways (The European Automobile Manufacturers' Association (ACEA) 2018, Eurostat 2018). In Australia, 2.33% of vehicles are heavy vehicles, but the freight moved by road accounts for 52% of tonnages moved and 42% of ton-kilometres travelled among the road, rail, sea and air networks (Australian Bureau of Statitics ABS 2002). The mass of a heavy vehicle ranges from 42.5 t to 147.5 t (Main Roads Western Australia 2016a), while a light vehicle is only 1.65 t and the gross vehicle mass (GVM) is generally lower than 4.5 t in Australia (Department of Transport - The Government of Western Australia 2016). Thus, due to the heavy masses, the impacts of heavy vehicles are much higher than light vehicles.

Furthermore, road infrastructure is influenced by complex factors, including road age and materials, surrounding climate environment, and socio-economic conditions, in addition to the traffic vehicles. From the perspective of geospatial analysis, the spatiotemporal non-stationarity of road and vehicle data has become increasingly critical with more accurate quantitative research, innovative technologies and smart management in recent years. The stationarity means that the spatiotemporal law of a spatiotemporal random field is invariant across the study area and period. Strict stationarity is difficult to test, and thus, secondary-order stationarity is commonly assumed in geospatial analysis, which only requires the first two moments of the spatiotemporal process. In traditional pavement engineering and construction management, the variations of road and vehicle data are usually considered to be stationary during the road planning, construction and maintenance phases. In different places and periods of the whole life of roads, the variations of the values of road and vehicle attributes are regarded as a constant. However, the geospatial objectives are usually non-stationary due to the specific spatiotemporal characteristics. For the road and vehicle data, non-stationarity is a common phenomenon in that performance varies in different places with diverse climates and ecological environments, and during various periods with associated seasonal effects, long-term trends and short-term fluctuations (Qiu et al. 2013). Ignoring the spatiotemporal non-stationarity of road and vehicle data might lead to the reduction of road life. Meanwhile, the lack of the knowledge on the impact of local climate, environment and socio-economic conditions on road can lead to uniformed and less effective strategies for road maintenance.

Finally, how to describe more aspects and provide more information of road infrastructure performance still represents an area of great need, even though data on additional indicators can be now collected through the development of sensing and monitoring techniques. Two questions that are important to researchers and practitioners need to be answered: which indicators are more reasonable and accurate in capturing road performance and how to develop overall indicators that can reflect the most relevant information from the monitoring data? To answer these questions, geospatial multi-criteria decision making (MCDM) is utilized for computing overall indicators and making decisions on indicator selection. Different from previous MCDM approaches, monitoring data for multiple indicators and geospatial information associated with road infrastructure performance will be taken into account in this study.

1.2 Scope

This study focuses on applying developed geospatial models for the analysis and decision making of road and vehicle management. The scope of this study is defined from three aspects: key issues, data and methods. First, the key issues to be address include how to quantify the traffic environmental impacts of heavy vehicle freight transportation, and what are the impacts. Since the issues are essential for practical decision making of industries, data analysis, professional knowledge of engineering and management and practical experiences should all be considered in the study. Second, this study is a data-driven research, and data sourced from multiple sources are generally converted to geospatial data statistical and spatial statistical data analysis. Finally, for more effective and accurate analysis and decision making, proposing developed geospatial models are critical for data analysis in the study.

1.3 Objectives

The aim of this research is to develop a methodology incorporating geospatial models for mapping the traffic environmental impacts of heavy vehicle freight transportation. This methodology will be applied using a geographically regional, flexible, and accurate multi-criteria decision making (MCDM) model of road and vehicle management. To achieve this outcome, four objectives are established:

(1) To critically understand road infrastructure performance and factors that have influence on pavement from a GIS perspective. First, the burden of road maintenance from heavy vehicles, the comprehensive impacts of multi-source factors on road infrastructure performance, and the geospatial decision making approaches for road infrastructure management will be reviewed. In addition, in order to better satisfy users' requirements in practical road and vehicle management, the BIM-GIS integration, which is an emerging platform to merge the strong parts of BIM and GIS, will also be reviewed and analysed from the aspect of spatio-temporal statistics.

(2) To accurately investigate heavy vehicle impacts on the burden of road maintenance. The line segment-based spatial prediction models will be developed and the road maintenance burden caused by different types of vehicles will be evaluated.

(3) To investigate comprehensive impacts of multi-source variables on road infrastructure performance. The accurate and geographically local impacts of vehicles, climate and environmental conditions on road infrastructure performance will be investigated.

(4) To develop geospatial MCDM methods for transportation authorities using flexible, accurate and geographically regionalised decisions for road and vehicle management, such as road performance assessment and road maintenance. The usability and effectiveness of the developed models and decisions are validated through both statistical validations and the comparison with the real defects of pavement.

1.4 Significance

The following three main contributions can be obtained from this research:

(1) **An innovative research program developing geospatial models for accurate spatial analysis of road, traffic and the surrounding environment problems.**

This research innovatively develops geospatial models for the analysis of road and traffic issues. In this research, spatial heterogeneity of line segment based spatial data is investigated, and a series of segment-based spatial models are proposed. Compared to previous methods, geospatial models developed in this research could help describe and accurately map traffic and environmental impacts in terms of segment-based observations, which is one of the primary theoretical contributions of this research. Due to the improvement of geospatial models and multi-source variables, the prediction and estimation accuracy of the impacts of heavy vehicle freight transportation on road infrastructure performance will be significantly improved. Meanwhile, the models address the problems of multiple traffic variables, their nonlinear relationships with the impacts, spatial variability, spatial non-stationarity, and segment-based spatial observations, which are all integral parts of the road and traffic analysis that have been overlooked by previous studies.

(2) **The development of flexible and accurate heavy vehicle freight transportation related decision-making approaches.**

Freight transportation by heavy vehicle is critical for the development of industries, but it usually produces road damage, rapid road aging and increased road maintenance burden and cost. Thus, it is necessary to establish flexible and accurate decisions about road and heavy vehicle management. Data-driven model-based spatial MCDM approaches that are able to accommodate uncertainty are proposed for spatial data supported decision making. The proposed methods can provide accurate and regional impact maps of heavy vehicles under various scenarios. The maps can support flexible decision making, such as accurate decisions on road asset management. Meanwhile, geospatial decisions support more effective monitoring and more accurate analysis of road infrastructure performance.

(3) **The optimisation of the road construction and management from a geospatial perspective.**

This research provides data-driven spatial analysis methods and more accurate datasets for road construction and management. For easy use of the proposed methods, software to implement the proposed spatial analysis methods is developed. The developed R packages can be freely downloaded and applied by users. In addition, this research integrates construction and procurement information from project-based BIM with the geospatial analysis and decision making for road and vehicles management. This is an important theoretical contribution for construction management. It can help industry to optimise road construction and management through relevant strategies, such as selecting the appropriate types of heavy vehicles, delivery routes and time sequencing to match the available road infrastructure.

1.5 Thesis structure

The remaining thesis is organized as in Figure 1-1 and the details are explained as follows.

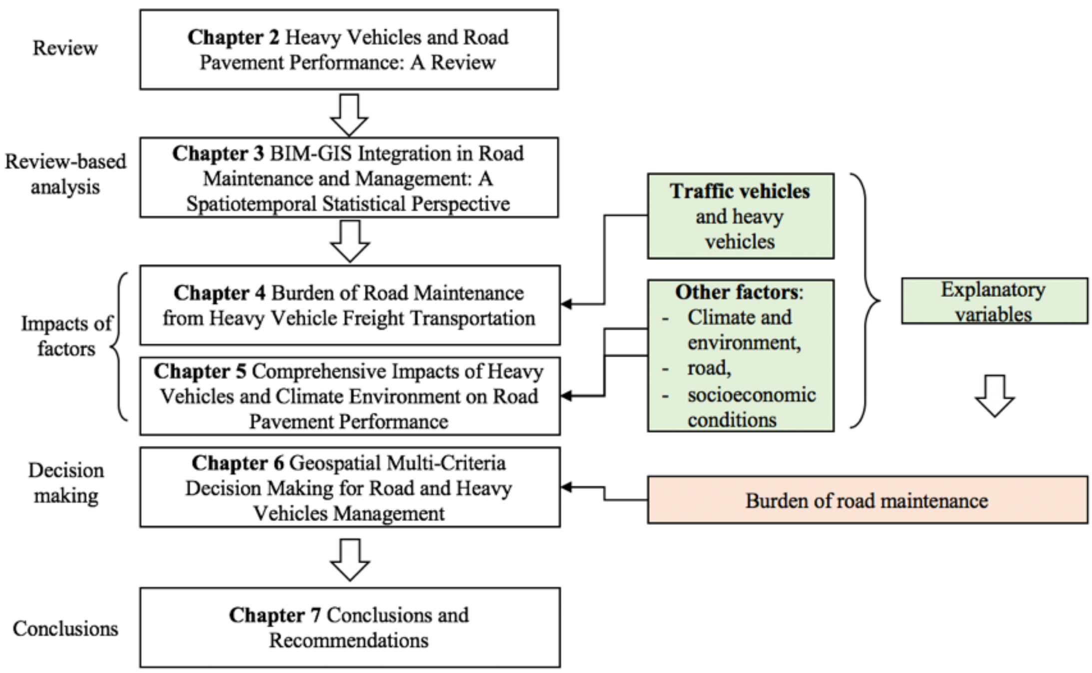

Figure 1-1. Structure of thesis and relationships of chapters

Chapter 2 reviews the background and methods of traffic vehicles studies and the assessment of road infrastructure performance.

Chapter 3 explores the trends and opportunities of implementing BIM-GIS integration in road construction and management from a spatiotemporal statistical perspective.

Chapter 4 analyses the burden of road maintenance through segment-based spatial prediction of traffic volumes and vehicle masses. Segment-based ordinary kriging (SOK) and segment-based regression kriging (SRK) methods are proposed for spatial prediction and burden estimation.

Chapter 5 presents the comprehensive impacts of various factors from multiple sources on road infrastructure performance using segment-based spatial stratified heterogeneity analysis. A segment-based geographical detectors model is utilized in the exploration of factors.

Chapter 6 computes an overall relative indicator for describing road infrastructure performance and compares the effectiveness and accuracy of different indicators using a data-driven model-based fuzzy spatial multi-criteria decision making (MFSD) approach.

Finally, Chapter 7 concludes the thesis and recommends future research directions.

Chapter 2 Heavy Vehicles and Road Pavement Performance: A Review

In this chapter, previous work about the impacts of heavy vehicles on the traffic environment and the quantitative analysis methods are reviewed. The review aims to investigate the methods of previous research and to identify the gaps and potential for future development. It can provide a comprehensive understanding of the background and knowledge base in multiple fields of this research. The review is organized as follows. Section 2.1 reviews the background and methodology for assessing the impacts of heavy vehicle freight transportation on the burden of road maintenance. Section 2.2 presents a review of the comprehensive impacts of heavy vehicles and climate environment on road pavement performance. In Section 2.3, from the perspective of decision making, previous studies about the quantitative analysis of geospatial multi-criteria decision making for road and heavy vehicle management are reviewed. Finally, the trends and benefits of BIM-GIS integration in traffic environment analysis and management are reviewed in Section 2.4.

2.1 Burden of road maintenance from heavy vehicle freight transportation

Road transportation is one of the primary factors of road pavement damage that links the burden of road infrastructure maintenance. To assess the burden of road maintenance, the total masses of vehicles on the road network should be estimated. Due to various traffic conditions, such as types and volumes of vehicles, the masses of vehicles are distinct on different road segments. Thus, it is necessary to accurately estimate and predict traffic volumes for different types of vehicles and on various road segments across the road network to quantify the burden of road maintenance.

Accurate spatial prediction of traffic volumes is of great importance for transportation analysis, planning and decision making. A wide range of methods have been applied for spatial prediction issues in the fields of road and traffic planning utilizing uncounted traffic data of road segments (Zou et al. 2012, Wang and Kockelman 2009, Zou et al. 2011). These studies can be divided into two categories:

statistical approaches and imaging approaches. Statistical approaches include studies such as multiple regression (Yang, Wang, and Bao 2011, Lowry 2014), time-series analysis (Tang et al. 2015, Tan et al. 2013), the U.S. Federal Highway Administration (FHWA) procedure (Rossi, Gastaldi, and Gecchele 2014, Guide 2012), machine learning algorithms (Islam 2016) and geostatistical methods (Selby and Kockelman 2013). Imaging approaches provide predictions with the help of image data such as light detection and ranging (LiDAR) data (Toth, Barsi, and Lovas 2003) and high-resolution remote sensing data (Jiang, McCord, and Goel 2006, McCord et al. 2002).

Among these approaches, geostatistical or kriging-based methods are very advantageous in providing insights into traffic behaviours across large spatial scales by exploring spatial local correlations. These methods are a series of the best linear unbiased estimators for spatial data with expected bias of zero and minimized expected interpolation error, and can provide both predictions and their estimated uncertainty. Thus, compared with other models, their predictions tend to be more accurate and reliable. Comparison studies reveal that universal kriging (UK) performs much better than non-spatial multiple regression (Zou et al. 2012, Selby and Kockelman 2011) and has a small improvement over geographically weighted regression (Selby and Kockelman 2013) in the spatial prediction of traffic volumes. In addition, traffic data, such as traffic speed and volume, are spatially continuous and autocorrelated, which means that traffic conditions at adjacent road segments are usually identical or similar. Traffic congestion may appear at road intersections especially in regions with dense human activities, and diffuse spatially leading to regional congestions (Zou et al. 2012). This phenomenon is explained as spatial autocorrelation that could be explored by geostatistical methods (Prasannakumar et al. 2011). For instance, geostatistical methods have been applied on traffic prediction issues including traffic count estimation (Selby and Kockelman 2011, Selby and Kockelman 2013), speed prediction of the traffic system (Hackney et al. 2007), travel time estimation (Miura 2010), congestion analysis (Prasetiyowati et al. 2016) and incident assessment (Molla, Stone, and Lee 2014).

However, all these studies utilize point-based spatial interpolation and they are not straightforward in traffic prediction. Actually, point-based methods are dominant for the interpolation of spatially continuous data over areas of interest, since spatial distribution data are often collected from point sources (Li and Heap 2014, Song et al.

2016, Song et al. 2015, Wang, Ge, Song, et al. 2014). But these methods simplify lines of road segments with various shapes and lengths as single points. This simplification process enables simple traffic modelling, but ignores the spatial characteristics and spatial heterogeneity of lines of road segments. Ignoring these elements leads to inaccurate predictions which can negatively affect decision making by road agencies. Thus, a segment-based interpolation method is necessary for predicting uncounted traffic data.

Previous studies have attempted to develop geostatistical methods for data with variable spatial support instead of traditional point support or regular pixel support of remotely sensed images. These methods include area-to-point kriging (ATPK) for estimation from area data to point data (Goovaerts 2009), area-to-area kriging (ATAK) for estimation of different areas (Pardo-Iguzquiza et al. 2011), top-kriging for estimation of data with variable spatial characteristics (Skøien, Merz, and Blöschl 2005), and their relevant development such as area-to-area regression kriging (ATARK) (Ge, Liang, et al. 2015) and area-to-point poison kriging (Goovaerts 2006). They have been utilized for addressing interpolation problems with irregular spatial support from runoff of river networks (Skøien, Merz, and Blöschl 2005, Skøien et al. 2014), geographical upscaling and downscaling (Ge, Liang, et al. 2015, Wang, Shi, et al. 2015, Zhang et al. 2017), population estimation (Liu, Kyriakidis, and Goodchild 2008), and mapping disease and health data (Asmarian et al. 2012, Goovaerts 2006, Asmarian et al. 2013). However, there are few research attempts to develop geostatistical interpolation models for traffic prediction with the integration of the irregular shape of road segments.

As an important continuous and regular construction task, cost effective road maintenance greatly relies on accurate traffic volume predictions. Road maintenance becomes increasingly critical for social and economic development, especially for safe, accessible and serviceable travel and freight transportation. The primary objectives of maintenance decisions of road networks include determining the road segments to be repaired, repair periods and treatment strategies (Chan, Fwa, and Tan 1994). Among these works, road segment based maintenance burden analysis is a key evidence and foundation for engineering studies on road damage (Fakhar and Asmaniza 2016), evaluation of environmental impacts (Min et al. 2016) and construction management of road maintenance (Gao, Zhang, and Li 2016). The gradual cracking and pulverization of road surfaces is usually caused by cumulative vehicle masses, especially trucks or heavy vehicles (Bilodeau, Gagnon, and Doré 2017, Underwood et al. 2017), and the penetration of the road surface by saline groundwater (Dasgupta et al. 2014). In addition, road damage varies by location, since the degree and speed of the impacts of cumulative vehicle masses vary on different roads that primarily serve passenger or freight transportation, and the impacts of groundwater salinization are highly variable across space depending on the local volume of water, and the age and composition of road materials. Previous studies have stressed the importance of burden estimation of road maintenance due to its link with maintenance cost, but few of them accurately and geographically predict the burden distributions at segment level.

2.2 Comprehensive impacts of heavy vehicles and climate environment on road pavement performance

The condition of road infrastructure is affected by numerous factors and varies greatly on different roads. Road infrastructure is critical to the well-being and economic health of all nations, so a large number of civil investments are made on road construction and maintenance (Main Roads Western Australia 1996, Underwood et al. 2017). The Australian Government spends more than $7 billion for maintaining and renewing road infrastructure every year (Commonwealth Grants Commission - Australian Government 2011), which accounts for about half of the aggregated public roads budget in Australia (Department of Infrastructure and Transport - Australia Government 2011). Road infrastructure plays an essential role in both public travel of passengers and freight transportation. Main roads supported 77.4% of domestic passenger travel (300.7 billion passenger kilometres (bpkm)) and 31.7% of domestic freight transportation (213.9 billion tonne kilometres (btkm)) during 2015-16 financial year in Australia (Department of Infrastructure and Regional Development - Australia Government 2017). The main roads of Australia were primarily built in since 1940s, when the factors affecting pavement conditions were seldom considered in the road construction process. In fact, numerous factors, including traffic conditions, climate and environment, and the characteristics of the pavement itself, have sophisticated and significant influence on pavement condition (Neumann et al. 2015, Ede 2014). Ignoring these factors in road construction and pavement materials selection may lead to a cumulative burden, premature damage, reduction of longevity and increased costs for road maintenance (Underwood et al. 2017, Wang et al. 2018). Thus, researchers have started to pay attention to the quantitative analysis of the impacts of various factors on pavement conditions in recent years. Pavement conditions are usually monitored and analysed using indicators of pavement infrastructure performance, such as deflections (Salour and Erlingsson 2013, Flintsch et al. 2013), roughness (Bridgelall 2013, Shah et al. 2013) and cracking (Solla et al. 2014, Yang and Deng 2017).

Vehicles and climate are two primary factors of pavement infrastructure performance concerned in recent research. Impacts of vehicles on pavement performance are from multiple aspects. Roads with high traffic volumes may face higher risk of pavement damage and higher cost of road maintenance (Smith and Peshkin 2011). Heavy vehicles produce substantial cumulative vertical stress on pavement due to their heavy mass (Steenkamp, Berman, and Benade 2016, Lee and Peckham 1990). Traffic mass overload can also increase risks of pavement damage and pavement repair costs, compared with vehicles under legal loads (Pais, Amorim, and Minhoto 2013). For climate factors, previous research generally uses temperature and precipitation as the direct and most important factors for pavement performance assessment. High temperatures and temperature variations usually lead to relatively large deflections (Lukanen, Stubstad, and Briggs 2000), slab, alligator and transverse cracking (Yu et al. 1998, Mohd Hasan, Hiller, and You 2016), strain rate reduction of asphalt pavement (Yin et al. 2016), permanent deformation (Mohd Hasan, Hiller, and You 2016) and increased pavement repair costs (Fletcher et al. 2016). Studies in the United States show that the longitudinal cracking of pavement is greatly influenced by temperature and precipitation, especially in wet climate areas where the expansion of frozen water contributes to cracking (Mohd Hasan, Hiller, and You 2016). Precipitation also may decrease pavement life (Mndawe et al. 2015) due to premature damage of materials and structure.

To explore the impacts of the factors on pavement infrastructure performance, two categories of methods have been commonly utilized in previous studies, including engineering methods and statistical methods. A widely used engineering method is the Pavement Design Mechanistic-Empirical (ME) model, which can calculate pavement performance variations resulting from climate change, traffic, pavement structure and materials, and is primarily applied on flexible and proper pavement design

(Underwood et al. 2017, Chatti et al. 2017, Gu et al. 2017, Yang, You, et al. 2017). The advantage of the method is that the expected performance and life of pavement can be estimated by involving parameters related to pavement structure and materials (Priest and Timm 2006, Li, Mills, and McNeil 2011). Another category of methods involves data-driven statistical methods, such as correlation analysis, statistical tests and regressions. For instance, Pearson correlation analysis and analysis of variance (ANOVA) are applied on assessing the effects of temperature and precipitation on pavement distresses, including various forms of cracking, rutting, pavement deformation and roughness (Mohd Hasan, Hiller, and You 2016). A seemingly unrelated regression model is utilized to study the impacts of the aggregate number of heavy vehicles on the side force, roughness and profile depth of pavement (Caliendo, Guida, and Pepe 2015). However, spatial heterogeneity is seldom considered in the above two categories of methods, even though pavement infrastructure performance is a typical geospatial problem. A major gap in the few considerations of spatial heterogeneity is that pavement observation data are distributed along line segments of the road network, which is different to traditional point or areal geographical observations distributed across the whole space and designed to capture the full range of variation of pavement condition and performance.

One of the primary objectives of spatial analysis is to explore spatially varied and local impacts of factors on geographical issues (Song et al. 2017, Song et al. 2016, Ge, Song, et al. 2017, Song et al. 2015, Cai, Huang, and Song 2017b). In this study, segment-based spatial stratified heterogeneity analysis is utilized to deal with the segment-based data and consider spatial heterogeneity in the assessment of pavement infrastructure performance. Segment-based spatial stratified heterogeneity analysis integrates optimal discretisation of segment-based data and the geographical detector. Optimal discretisation aims at exploring the best combination, such as the discretisation method and number of breaking intervals, for discretising continuous variables. The geographical detector is a spatial statistical method that can analyse relationships between geographical variables based on spatial variance and geographical strata. The method was originally utilized to explore spatial stratified risk factors of disease (Wang et al. 2010). The method is increasingly used in spatial stratified heterogeneity analysis in broad fields, including public health (Ge, Zhang, et al. 2017), land use (Gao et al. 2017), carbon emissions (Fang et al. 2017), air pollution

(Zhou, Chen, and Wang 2018), economy (Yang, Hu, et al. 2017), etc., due to a series of advantages in spatial analysis. A primary advantage is that no linear assumptions are required for the relationships between explanatory and response variables, and for the relationships between pairs of explanatory variables, since the method objectively reveals the spatial associations between response and explanatory variables (Wang 2017). In addition, interactive impacts between two variables or among multiple variables can be quantified with the geographical detector (Wang, Zhang, and Fu 2016, Ju et al. 2016). Finally, the types and stratifications of explanatory variables are flexible, where continuous variables can be discretised to categorical variables.

2.3 Geospatial multi-criteria decision making for road and heavy vehicles management

2.3.1 How to characterize infrastructure performance

Road infrastructure is critical for passengers and freight transportation, and it is one of the predominant factors for socio-economic development. In general, the theoretical life of road infrastructure is about 25 – 40 years, which varies in different nations and for different types of roads (Main Roads Western Australia 1996). However, an increasing number of recent studies realize the lifespan might be significantly reduced due to various reasons, such as high vehicle mass loads and climate change, causing dramatically elevated and spatially uneven distribution of risks of road damage. Thus, how to more accurately monitor and evaluate the geographically local performance of road infrastructure raises researchers' attention. A practical and widely used approach is using one or more indicators to assess road infrastructure performance, since the monitored data can directly and accurately reflect road performance such as structural and functional conditions. The performance indicators play an important role in the design, construction, maintenance, management and ensuring safety and reliability during the whole life cycle of road infrastructure (Council 1995).

The measures of road infrastructure performance are commonly used to quantify the quality of service to road users. Road infrastructure performance is generally measured from four perspectives: pavement condition, traffic capacity, safety and population accessibility (Council 1995). Pavement condition measures reveal the structure and functional condition of the road surface (Dong and Huang 2015, Wadalkar, Lad, and Jain 2018). The traffic capacity of roads includes congestion of traffic flows, travel time, and the ratio of actual traffic volume to volume capacity (Çolak, Lima, and González 2016). Safety measures can examine if accident rates have associations with the road design and pavement conditions (Anastasopoulos, Sarwar, and Shankar 2016). Population accessibility measures are used to quantify the ease and resources with which people can access facilities and services through road transport (Song, Tan, et al. 2018). All the above measures are critical for the design, planning, maintenance and optimization of both public facilities and road infrastructure. This study focuses on the pavement condition measures. Pavement performance can be evaluated from multiple aspects, such as structural and functional indicators (Wadalkar, Lad, and Jain 2018). From the perspective of industrial practice, pavement condition measures are usually classified into three categories: deformation distresses, surface distresses and texture distresses. Commonly used deformation distress indicators include deflection, curvature, roughness and rutting (Ferreira et al. 2011, Anastasopoulos et al. 2012, Sultana et al. 2018, Lin, Cho, and Kim 2016). Surface distresses usually measures the cracking, ravelling, different types of potholing and edge breaks on the pavement surface (Jain, Jain, and Jain 2017, Mullin, Liu, and McHattie 2014, Thube 2012). Pavement surface texture distress can be measured by the flushing and polishing conditions, texture depth and skid resistance (Kennedy, Young, and Butler 1990, Asi 2007, Lee, Mannan, and Wan Ibrahim 2018, Schnebele et al. 2015, Carmon and Ben-Dor 2018). These indicators are widely applied for monitoring, maintenance and management of road pavement. However, a single indicator generally cannot reflect the overall and comprehensive condition of pavement, even it has advantages for assessing pavement performance from one aspect. In fact, it is very difficult and challenging to have an overall indicator that can reflect every aspect of pavement performance that is accurate, informative and satisfactory for users (Council 1995). The overall indicators are usually more effective for assessing pavement performance compared with single indicators (Shah et al. 2013).

In addition to the structural and functional road conditions that can be revealed by the performance indicators, road infrastructure performance is also linked with the properties of roads and their surrounding environment (Schweikert, Chinowsky, Kwiatkowski, et al. 2014, Schweikert, Chinowsky, Espinet, et al. 2014, Chinowsky et al. 2015, Melvin et al. 2017). On one hand, the continuous increase of traffic volumes brings a huge burden for road infrastructure. In 2015, the global number of motor vehicles reached 923.6 million, which is 1.68 times the number in 2000 and 6.61 times the number in 1965 (Williams, Davis, and Boundy 2017, Davis, Diegel, and Boundy 2015). The annual rate of increase decreased from 8.44% in 1965 to -0.10% in 1993, and it is maintained at around 0% until 1999, but has started to increase since 2000. The annual average rate of increase during 2000 to 2015 is 5.39%, where the rate reaches 10.58% and 11.08% in 2000 and 2014, respectively. Meanwhile, the annual average increase of the number of vehicles per capita is 1.27 from 1965 to 2000, but it reaches to 2.71 from 2000 to 2015, and 4.25 from 2010 to 2015 (Williams, Davis, and Boundy 2017). On the other hand, the increased burden of road infrastructure also comes from the pronounced variability of climate change and extreme climate with growing frequency and intensity. The increased vulnerability of road infrastructure due to climate change is explored in a study in Alaska, United States. It reveals that climate change related road damage may cause at least 4.2 billion USD and an extra 1.3 billion USD by greenhouse gas emissions during this century (Melvin et al. 2017). Studies in Asia and Africa also show the huge costs of climate change related road damage. For instance, during this century, the average annual decadal costs for road infrastructure maintenance may reach 7.6 billion, 2.0 billion, 0.6 billion, and 86.3 billion USD in China, Japan, South Korean and Pan-Africa, respectively (Westphal, Hughes, and Brömmelhörster 2015, Chinowsky et al. 2011, Strzepek et al. 2012). Thus, predictive maintenance and proactive and resilience adaptions are required to reduce the impacts of climate change on road damage and the burden of road infrastructure maintenance (Melvin et al. 2017, Schweikert, Chinowsky, Kwiatkowski, et al. 2014).

2.3.2 Literature review of methodology

The MCDM is an effective approach for dealing with complex decision-making problems. It can integrate the performance of decision alternatives across multiple criteria from various sources to derive a compromise solution (Opricovic and Tzeng, 2004). The MCDM is gradually improved by combining with methods and techniques in specific professional fields. To involve geospatial data and methods in decision making, the GIS-based MCDM (GIS-MCDM) method is proposed (Malczewski, 2006). In addition, the fuzzy MCDM method is developed to quantify the uncertainty in the decision making (Suárez-Vega and Santos-Peñate, 2014). Compared with traditional decisions based on the knowledge and experience of experts, data and model drive decision-making methods rely more on the data and data analysis models, and they can effectively address sophisticated decision-making problems (Sari and Zarlis, 2018). In this section, we review the literature and concepts associated with the methodology to be applied in the research, including the MCDM method, the GIS-MCDM method, the fuzzy MCDM method and the data and model driven decision-making methods.

The MCDM is a complex and dramatic process consisting of goals definition, available alternatives, various criteria and the preference structure of decision makers who evaluate the alternatives in terms of the criteria (Opricovic and Tzeng 2004). The commonly used MCDM methods include the AHP method (Saaty 2013, Saaty and Decision 1990), TOPSIS method (Hwang and Yoon 1981), VIsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR) method (Opricovic 1998), multi-objective optimization on the basis of ratio analysis (MOORA) method (Brauers and Zavadskas 2006), weighted aggregated sum product assessment (WASPAS) method (Zavadskas et al. 2012), ELimination Et Choix Traduisant la REalité (ELECTRE) method (Benayoun, Roy, and Sussman 1966, Roy 1968, Roy and Bertier 1971, Roy and Bertier 1973, Roy 1978), preference ranking organization method for enrichment evaluation (PROMETHEE) method (Brans and Vincke 1985, Brans, Vincke, and Mareschal 1986), etc. Among the MCDM methods, the AHP and TOPSIS are more practical for applications compared with other methods due to the simplicity and ease of utilization (Sánchez-Lozano et al. 2013). The AHP method develops a hierarchical structure of objectives, alternatives and criteria, and compares alternatives in terms of the relative importance of the criteria and alternatives under each criterion using a pair-wise comparison method (Saaty 2013). The TOPSIS method defines that the optimal alternative should have "the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution" (Opricovic and Tzeng 2004), but it does not perform pair-wise comparisons among criteria and alternatives under each criterion.

Further, GIS-MCDM is a critical spatial analysis method in geospatial decision making that integrates information stemming from multiple sources, including both spatial and non-spatial data (Feizizadeh et al. 2014, Sánchez-Lozano et al. 2013). GIS is a broad field for dealing with geospatial data and applications, and is used for the storage and management of spatial and spatiotemporal data, visualization, spatial analysis and decision making (Berry 1996b). Especially, GIS has advantages over spatial and spatiotemporal characteristics analysis, factors exploration, prediction and simulation (Song et al. 2017). The combination of GIS and MCDM methods gradually becomes a framework for addressing sophisticated decision-making issues through hierarchical organization and construction of spatiotemporal relationships for the elements and components of the objectives (Malczewski 2006). Due to uncertainty in the information and processes of decision, fuzzy theory is increasingly utilized in GIS-MCDM studies, such as land use evaluation, water resources management and infrastructure allocation issues (Zhang et al. 2014, Feizizadeh et al. 2014, Esmaelian et al. 2015, Bingham, Escalona, and Karssenberg 2016, Malczewski and Rinner 2005). Fuzzy set theory uses membership functions to describe the preference comparisons of the attributes of interest (Chang 1996). The fuzzy set theory can describe uncertainty of criteria using the degree of memberships for criteria in the MCDM process (Jiang and Eastman 2000, Suárez-Vega and Santos-Peñate 2014). The fuzzy MCDM approach provides greater flexibility for the evaluation in terms of geospatial data and the GIS-MCDM process (Jelokhani-Niaraki and Malczewski 2015).

Meanwhile, compared with traditional decision making methods, data and model driven decision-making approaches and support systems can deal with the dramatically elevated complexity and uncertainty in the decision-making issues, especially the mega decisions, interdisciplinary and cross-domain problems (Power and Sharda 2007, Backer, Mertsching, and Bollmann 2001, Hedgebeth 2007). Traditional decision making methods are driven by knowledge from experienced decision makers and experts, so the accuracy of decisions depends largely on the decision makers, and the biases and uncertainties caused from human factors are still a critical problem (Power 2008, 2000). To reduce the biases and uncertainties from human factors, data and model driven methods aim at supporting decisions using data analysis models. Commonly used quantitative models of data and model driven decision making include regression models, classification models, prediction models and simulation models (Mandinach 2012, Sari and Zarlis 2018). However, data and model driven decision approaches are still at initial stage of development and have great potential. First, the framework and processes of data and model driven decision making are a priori, and they can be varied in different problems and fields. In addition, the mainstream of current quantitative models of data analysis are linear and non-linear statistical models, which are practical and direct to derive the relationships between criteria and alternatives, but these methods are still limited in addressing sophisticated issues, especially the spatial and spatiotemporal problems examining during the GIS-MCDM process. Finally, most of previous studies use a single or a limited number of statistical models to explore the relationships between criteria and alternatives in data and model driven decision making. Due to the differences in mathematical concepts of various statistical models and the parameters, the results of association functions might be different, even some of them might be identical or similar. Thus, it is necessary to apply more models to evaluate the relationships between criteria and alternatives to improve the accuracy and reduce the uncertainties of decisions.

2.4 Trends and opportunities for BIM-GIS integration in the architecture, engineering and construction industry

Worldwide growth of cities with rapid urbanization and global climate change are the two most critical issues in the current world (Grimm et al. 2008, Satterthwaite 2009, McDonald et al. 2011). The concept of a smart sustainable city is an innovative concept that has been widely considered since the mid-2010s and aims at improving the quality of life of present and future generations under the conditions of urbanization and global climate change (Höjer and Wangel 2015, Kramers et al. 2014, Bibri and Krogstie 2017). With the wide utilization of information and communication technologies (ICTs) and the internet of things (IoT), urban services will be more efficient and cities will be more competitive for their socio-economic, environmental and cultural conditions (Griffinger et al. 2016). Thus, a smart sustainable city is characterized by widely used technology and comprehensive improvement of the sustainability of urban lifestyle, which requires massive and multi-source data for the use of technologies and management.

The integration of building information modelling (BIM) and geographic information systems (GIS) is a strong support for smart sustainable cities due to capabilities in data integration, quantitative analysis, application of technologies and urban management (Ma and Ren 2017, Fosu et al. 2015, Yamamura, Fan, and Suzuki 2017b). BIM-GIS integration in construction management has been a new and fast developing trend in recent ten years, from research to industrial practice. BIM has advantages in rich geometric and semantic information through the building life cycle (Volk, Stengel, and Schultmann 2014), while GIS is a broad field covering geovisualisation-based decision making and geospatial modelling (Berry 1996a). Their respective advantages have been discussed in some of the previous review articles (Liu et al. 2017, Pauwels, Zhang, and Lee 2017, Ma and Ren 2017). BIM-GIS integration is to integrate the strong parts of both BIM and GIS for building and city modelling. During the past ten years, BIM-GIS integration has been applied in multiple cases such as visualization of construction supply chain management (Irizarry, Karan, and Jalaei 2013), emergency response (Teo and Cho 2016, Xu et al. 2016, Wu and Zhang 2016), urban energy assessment and management (Salimzadeh, Sharif, and Hammad 2016, Romero et al. 2016, Costa et al. 2016), heritage protection (Yang, Koehl, et al. 2016, Bento et al. 2016), climate adaption (Hjelseth and Thiis 2009) and ecological assessment (Zhou and Castro-Lacouture 2016).

In previous BIM-GIS integration studies, researchers spent a lot of efforts on the integration technologies. Various BIM-GIS integration methods are proposed to address different problems (Pauwels, Zhang, and Lee 2017, Liu et al. 2017). For the integration pattern, more than half of the researchers prefer to extract data from BIM to GIS, and others integrate GIS data to BIM systems or integrating both BIM and GIS data on a third-party platform (Ma and Ren 2017). For instance, Industrial Foundation Class (IFC) and City Geography Markup Language (CityGML) are two of the most popular and comprehensive standards for exchanging semantic 3D information and geographic data for BIM and GIS respectively, and they are the primary standards for BIM-GIS integration (Gröger and Plümer 2012, Deng, Cheng, and Anumba 2016b, Hijazi et al. 2010). During the integration process, some significant details are lost due to the extraction and simplification of data from one system to another (Yuan and Shen 2010). To avoid information losses, the unified building model (UBM) is proposed to cover information of both IFC and CityGML models (El-Mekawy, Östman, and Hijazi 2012).

Even though many technical issues related to the integration of BIM and GIS have been fully or partially addressed, few theoretical studies address how to fully integrate the respective strengths of BIM and GIS for further quantitative analysis. Spatial or spatio-temporal statistical modelling for the analysis of patterns and exploration of relationships is regarded as the central function of GIS (Bailey 1994, Marshall 1991, F Dormann et al. 2007, Wang, Zhang, and Fu 2016, Wang et al. 2012), but it is scarcely mentioned in BIM-GIS integration studies. During the past thirty years, spatio-temporal statistical modelling has been widely applied to geosciences including geology, geography, agriculture, ecology, atmospheric science, hydrology, etc. (Fischer and Wang 2011), and location-based studies in other fields such as urban planning (Páez and Scott 2005, Chun and Guldmann 2014, Cai, Huang, and Song 2017a), public health (Wang et al. 2010, Yang, Xu, et al. 2017) and social science (Ge, Yuan, et al. 2017, Ren et al. 2017, Chen and Ge 2015, Liao et al. 2017). From the perspective of the architecture, engineering and construction (AEC) industry, with the wide application of BIM, especially the collection of massive data, accurate mathematical modelling is required for the analysis and assessment of each stage of AEC industry, quality, cost, progress, safety, contract and information management, and coordination of various sectors.

Chapter 3 BIM-GIS Integration in Road Maintenance and Management: A Spatiotemporal Statistical Perspective

3.1 Introduction

This chapter aims to summarize applications of BIM-GIS integration and propose the potential of its future development in the AEC industry from a spatio-temporal statistical perspective.

In this thesis, the applications of BIM-GIS integration to characterize its evolution from three aspects are reviewed, (1) applications of BIM-GIS integration in the AEC industry during past ten years, (2) history of BIM-GIS integration from the perspective of surveying and mapping, and (3) comparative study of the evolution of GIS, BIM and integrated BIM-GIS. The analysis of evolution of BIM-GIS integration enables further and deep understanding of the central functions and primary scope of BIM, GIS and their integration. Based on the analysis, this review aims at summarizing the trends of applying BIM-GIS integration in the AEC industry and proposing potential opportunities of BIM-GIS integration from the perspective of spatio-temporal statistical modelling. As a result, we propose three hypotheses for future development of BIM-GIS integration.

This review-based analysis is structured as follows. Section 3.2 summarizes the methodology of review for the status quo of current applications of BIM-GIS integration globally. Section 3.3 analyses the evolution of BIM-GIS integration from the three aforementioned aspects. Section 3.4 discusses future trends and proposes potential opportunities of BIM-GIS integration in the AEC industry. Section 3.5 concludes this analysis.

3.2 Methodology of review

In this thesis, the integration of BIM-GIS is reviewed to characterize the evolution of BIM-GIS integration. An evaluation of research and practical trends and gaps is undertaken in order to propose the future opportunities. To achieve this goal, the literatures is analysed from three aspects. First, the current application trends since the concept of BIM-GIS integration are explored. Publications associated with BIM-GIS integration are collected and statistically analysed. The literature is summarized according to multiple indicators including the annual number of publications, annual citation times, distribution of publications across countries/regions and universities/institutes, research areas the publications belong to, and the primary journals and conferences for BIM-GIS integration studies. The evolution of BIM-GIS integration needs to be described and the reasons why it has developed in this direction will be further discussed. Finally, the potential prospects, opportunities and drawbacks are evaluated from the spatio-temporal statistical perspective so that the functional analysis can be fully utilized in the practices of AEC industry.

Literature about BIM-GIS integration was retrieved from the Web of Science ™ Core Collection. Both journal and conference articles were retrieved. Journals are limited to Science Citation Indexed (SCI) or Social Sciences Citation Indexed (SSCI) journals, and conferences are indexed by the Conference Proceedings Citation Index-Science (CPCI-S) or Conference Proceedings Citation Index-Social Science & Humanities (CPCI-SSH). "BIM" and "GIS" are keywords with the operator of "AND" for searching the topic of the literature, which includes title, abstract, author keywords and keywords plus®, and the publication language is limited to English. As a result, 99 research articles were retrieved (before September 2017). Three articles among them were not related with BIM-GIS integration and they were removed. Thus, 96 articles concerning BIM-GIS integration were collected, including 36 articles from SCI/SSCI indexed journals.

3.3 Evolution of BIM-GIS integration

The evolution of BIM-GIS integration is characterized by three aspects: application evolution in AEC industry, history from the perspective of surveying and mapping, and comparison study of the evolution of GIS, BIM and integrated BIM-GIS. The three aspects of BIM-GIS integration evolution are discussed in the following subsections.

3.3.1 Application evolution in AEC industry

The evolution of BIM-GIS integration in the AEC industry reveals that BIM-GIS integration has moved from simple cases to deep considerations and complex applications.

Most of the early studies try to address technological problems of integration. In general, multiple integration methods are proposed to address various problems (Liu et al. 2017, Pauwels, Zhang, and Lee 2017). A mainstream of integration methods is extracting BIM data to the GIS context (van Berlo and de laat 2010, Liu et al. 2014). While, during this process, some significant details are lost (Yuan and Shen 2010). To address this problem, a unified building model (UBM) covering both IFC and CityGML models is utilized to avoid detail loss (El-Mekawy, Östman, and Hijazi 2012). In addition, to ensure the construction details, geometric topological and semantic topological modelling are applied on capturing 3D features (Li et al. 2016), such as the application of floor topology detection (Dominguez, Garcia, and Feito 2012). A series of methods are also proposed to ensure the interoperability of BIM and GIS, such as semantic web technology (Karan, Irizarry, and Haymaker 2016, de Farias, Roxin, and Nicolle 2015), semantic-based multi-representation approaches (Mignard, Gesquiere, and Nicolle 2011), implementation of prototypes (Hwang, Hong, and Choi 2013), and resources description framework (RDF) (Hor, Jadidi, and Sohn 2016).

After the initial development, researchers started to propose new standards and methods for building and urban database management. Concept of level of details (LoD) in CityGML is applied on the representation and management of buildings and building elements during BIM-GIS integration (Geiger, Benner, and Haefele 2015, Ryu and Choo 2015, Deng, Cheng, and Anumba 2016b). Studies also explain the techniques for the storage, query, exchange and management of spatial information (Musliman, Abdul-Rahman, and Coors 2010, Borrmann 2010, Isikdag, Zlatanova, and Underwood 2012, Zlatanova, Stoterand, and Isikdag 2012, Sergi and Li 2014, Ryzynski and Nalecz 2016). A web-based open source platform is considered as a well-behaved tool for the sharing and fusion of 3D information in digital buildings (Delgado et al. 2015, Isikdag 2015, de Farias, Roxin, and Nicolle 2015, Park and Kim 2016, Kunchev 2016). In addition to building and urban database management, comparison studies and comprehensive applications are performed to explore the advantages and disadvantages of 3D display methods and software, including 3D GIS, BIM, CAD, CityEngine, 3D Studio Max and SketchUp (Cengiz and Guney 2013, El Meouche, Rezoug, and Hijazi 2013, Jia and Liao 2017, Mijic, Sestic, and Koljancic 2017).

More specifically, publications are categorized based on their application areas and publication years to reveal the application evolution of BIM-GIS integration in the AEC industry (Table 3-1). Applications are classified into two categories according to the application object, a building or a city. The applications with the object of buildings are classified into four categories according to the construction phases, including planning and design, construction, operation and maintenance, and demolition. Results show that the application objects consist of both buildings and cities, which includes urban infrastructure. For applications with objects of buildings, 61% of the studies focus on the operation and maintenance phase but only a few studies explore the demolition phase.

Table 3-1. Application evolution of BIM-GIS integration in AEC industry

Application object		Building				City
Construction phase		Planning and design	Construction	Operation and Maintenance	Demolition	
Year	2008	Site selection (Isikdag, Underwood, and Aouad 2008).		Fire response (Isikdag, Underwood, and Aouad 2008); Web service (Lapierre and Cote 2008); Disaster scenarios (Lapierre and Cote 2008).		3D city (Doellner and Hagedorn 2008).
	2009	Climate adaptation (Hjelseth and Thiis 2009).				Urban renewal projects (Kim et al. 2009).
	2010		Urban renewal projects (Choi et al. 2010).			Urban facility management (Hijazi, Ehlers, and Zlatanova 2010, Hijazi et al. 2010) (e.g.

					road maintenance (Monobe and Kubota 2010)); urban design (Gil et al. 2010).
2011	Construction safety planning (Bansal 2011a); construction space planning (Bansal 2011b).	Visualization of construction time control (Elbeltagi and Dawood 2011).	Existing buildings maintenance (Godager 2011).		
2012		Highway construction management (Fu et al. 2012).	Emergency response (Zlatanova, Stoterand, and Isikdag 2012).		Urban crisis response (Chambelland and Gesquiere 2012); human activity and land use (Porkka et al. 2012)
2013	Site selection of solar panels (Andrey and Luiza 2013).	Visualization of construction supply chain management (CSCM) (Irizarry, Karan, and Jalaei 2013).	Indoor navigation (Isikdag, Zlatanova, and Underwood 2013); heritage protection (Bianco, Del Giudice, and Zerbinatti 2013).		Urban representation (Rua, Falcao, and Roxo 2013, Stojanovski 2013).
2014			Fire simulation and response (Chen, Wu, et al. 2014); heritage protection (Mezzino 2014); large building operation (Forsythe 2014).		Urban facility management (Mignard and Nicolle 2014) (e.g. traffic planning (Wang, Hou, et al. 2014)).
2015	Building design and preconstructi		Facility management (Kang and	Construction waste processing	Tunnel modelling (Borrmann et

	on operations (Karan and Irizarry 2015, Gocer, Hua, and Gocer 2015); building energy design (Niu, Pan, and Zhao 2015, Iadanza et al. 2015).		Hong 2015); indoor emergency response (Tashakkori, Rajabifard, and Kalantari 2015); heritage protection (Baik, Yaagoubi, and Boehm 2015, He et al. 2015).	(Liu et al. 2015).	al. 2014); energy assessment and management (Ronzino et al. 2015, Redmond, Fies, and Zarli 2015, De Hoogh et al. 2015); district modelling (Del Giudice, Osello, and Patti 2015).
2016	Building design (Kari et al. 2016).	Urban renewal projects (Gocer, Hua, and Gocer 2016).	Flood damage assessment and visualization (Amirebrahimi et al. 2016b, Lyu et al. 2016, Amirebrahimi et al. 2016a); indoor emergency response and route planning (Teo and Cho 2016, Xu et al. 2016, Wu and Zhang 2016); hazard identification and prevention (Ebrahim, Mosly, and Abed-Elhafez 2016, Hu et al. 2016, Ferrari and Sasso 2016); heritage protection (Yang, Koehl, et al. 2016, Bento et al. 2016); ecological assessment (Zhou and Castro-Lacouture 2016).		Traffic noise analysis (Deng, Cheng, and Anumba 2016a); walkability evaluation of urban routes (Kim et al. 2016); energy assessment and management (Salimzadeh, Sharif, and Hammad 2016, Romero et al. 2016, Costa et al. 2016); utility compliance checking (Li, Cai, and Kamat 2016).

2017	Lift planning of disassembling offshore oil and gas platform (Tan et al. 2017).	Resilient construction supply chain management (CSCM) (Wang et al. 2017).	Management of property interests (Atazadeh, Rajabifard, and Kalantari 2017).		Energy assessment and management (Yamamura, Fan, and Suzuki 2017a).

As can be seen from the annual variations, applications tend to be diverse and complex from 2008 to 2017. Emergency and disaster simulation, response and management is a typical and hot topic (Isikdag, Underwood, and Aouad 2008, Zlatanova, Stoterand, and Isikdag 2012, Lapierre and Cote 2008, Chen, Wu, et al. 2014, Tashakkori, Rajabifard, and Kalantari 2015). It has drawn more attention recently as there were nine publications related to this topic in 2016 (Amirebrahimi et al. 2016b, Lyu et al. 2016, Amirebrahimi et al. 2016a, Teo and Cho 2016, Xu et al. 2016, Wu and Zhang 2016, Ebrahim, Mosly, and Abed-Elhafez 2016, Hu et al. 2016, Ferrari and Sasso 2016). This topic is a typical BIM-GIS integration problem that should be addressed with both large spatial scale and detail considerations of construction components. Maintenance and renewal of existing buildings is studied since 2010 (Choi et al. 2010, Godager 2011). This topic has great potential in future studies, since there will be high demand in the future for maintenance and renewal of existing buildings as a result of the age profile of the global building stock in developed nations and urbanized regions in developing nations. Maintenance and renewal of existing buildings has been a great challenge for BIM and represents a lot of opportunities for BIM-GIS integration. Compared with the management of old buildings, construction planning and design is more about new buildings. Applications of BIM-GIS integration on planning and design include multiple aspects, such as site selection and space planning (Isikdag, Underwood, and Aouad 2008, Andrey and Luiza 2013), climate adaptation (Hjelseth and Thiis 2009), safety planning (Bansal 2011a), building design and preconstruction operations (Karan and Irizarry 2015, Gocer, Hua, and Gocer 2015, Kari et al. 2016), energy design (Niu, Pan, and Zhao 2015, Iadanza et al. 2015) and planning of disassembling process (Tan et al. 2017). The popular topics of applying BIM-GIS integration on buildings also include indoor navigation (Isikdag, Zlatanova, and Underwood 2013), heritage protection (Bianco, Del Giudice, and Zerbinatti 2013, Mezzino 2014, Baik, Yaagoubi, and Boehm 2015, He et al. 2015, Yang, Koehl, et al. 2016, Bento et al. 2016), construction supply chain management (Wang et al. 2017, Irizarry, Karan, and Jalaei 2013), mega projects management (Forsythe 2014), ecological assessment (Zhou and Castro-Lacouture 2016), etc. For the applications of BIM-GIS integration on cities, 3D urban modeling and representations (Doellner and Hagedorn 2008, Rua, Falcao, and Roxo 2013, Stojanovski 2013), urban facility management (Hijazi, Ehlers, and Zlatanova 2010, Hijazi et al. 2010), and emergency response (Chambelland and Gesquiere 2012) are the primary aspects at the beginning of the integration attempt. In recent years, more studies utilize BIM-GIS integration to characterize human activities and their relationships with cities, such as traffic planning and analysis (Wang, Hou, et al. 2014, Deng, Cheng, and Anumba 2016a), walkability analysis (Kim et al. 2016), and energy assessment and management (Ronzino et al. 2015, Redmond, Fies, and Zarli 2015, De Hoogh et al. 2015, Salimzadeh, Sharif, and Hammad 2016, Romero et al. 2016, Costa et al. 2016, Yamamura, Fan, and Suzuki 2017a).

The applications of BIM-GIS integration cover all construction phases of buildings, and city and urban infrastructure. In the applications, the strong parts of BIM and GIS are generally integrated for building and city modelling, but the respective functions of BIM and GIS utilized in these applications tend to be similar. BIM presents the rich geometric and semantic information of buildings, cities and infrastructure through the life cycle (Volk, Stengel, and Schultmann 2014). Meanwhile, GIS is commonly regarded as a 3D visualization system of built environment and urban system in current applications of BIM-GIS integration. The above summary of applications BIM-GIS integration reveals that current applications have three primary advantages. First, data and information with multiple spatial scales are integrated to address problems related to both construction components and built environment. This is also a starting point of using BIM-GIS integration. Second, the primary function of BIM has been applied that provides complete and detailed geometry and material information of building components. Finally, visualization-based analysis improves the efficiency and performance of construction management in AEC projects.

However, the applications are still limited in the use of integrated BIM-GIS, and the strengths of both BIM and GIS have not been fully integrated and utilized. First, the utilization of primary functions of GIS is very limited, since GIS is a broad field covering geovisualisation-based decision making and geospatial modelling (Berry 1996a) instead of a system of 3D visualization of built environment and cities.

Spatial and spatio-temporal statistical analysis are seldom considered and used in the current applications of BIM-GIS integration. Second, BIM provides geometry and semantic information of construction components, but the information of user requirements of AEC projects is rarely involved in BIM. In recent years, it is a necessary part of BIM applications to study and propose solutions of user requirements such as quality, time and cost management. Third, LoD is applied on the representation and management of buildings and building elements in IFC and CityGML models, but it has not been treated as the spatio-temporal attributes during the integration processes of analysis and decision making.

3.3.2 History from the perspective of surveying and mapping

Analysis of the application evolution of BIM-GIS integration indicates a trend to use integrated BIM-GIS to address diverse and complex problems in the AEC industry. Seen from the perspective of surveying and mapping histories, integrated BIM-GIS would have broader and deeper theories and methods for applications. Figure 3-1 shows the history of BIM-GIS integration from the perspective of surveying and mapping. GIS and BIM are the products of digitization of two sub-disciplines of surveying and mapping, geodesy and engineering survey. On one hand, a central function of GIS is to analyse patterns and explore relationships of spatial data, which are primarily collected by geodetic methods (Bailey 1994, Marshall 1991, F Dormann et al. 2007, Wang, Zhang, and Fu 2016, Wang et al. 2012). One of the primary products of field geodetic work is topographic maps with large spatial scales indicating terrain characteristics, infrastructure, buildings and land cover. After digitization of topographic maps, spatial data depicting natural attributes become data layers of GIS (Chang 2006). Further, due to the capability of spatial analysis, GIS becomes a science and system to analysis spatial data and have deep and comprehensive understanding of natural processes (Fischer and Wang 2011). On the other hand, BIM was originally used as a platform for model visualization, data exchange and analysis of digitized engineering drawings of buildings or infrastructure (Eastman et al. 2011). With wide applications from design to maintenance stages of construction management, BIM is changing the AEC industry (Wang, Sun, et al. 2015). BIM emerges as a system of creating, sharing, exchanging and managing building and urban information throughout the whole lifecycle among all stakeholders (Wang, Zhang, et al. 2015). Thus, in theory, beyond technology integration, i.e. platform or system integration, BIM and GIS have great potential to be integrated from multiple aspects including integration of database management, theories and methods, analysis and products, etc. For addressing urban problems, both BIM and GIS emphasize the utilization of ICTs and new technologies. In addition to the ecological, energy and environmental issues solved by integrated BIM-GIS, BIM is also associated with the sustainability of buildings and urban infrastructure through a series of new methods such as lean production (Peng and Pheng 2011b, Wu and Feng 2012, Peng and Pheng 2011a, Peng 2010), carbon emission assessment (Wu, Xia, and Wang 2015, Wu et al. 2016, Wu, Feng, et al. 2015, Wu et al. 2014, Wu et al. 2017) and green building design (Xia et al. 2014). Therefore, BIM and GIS can be integrated at various stages for analysis in AEC industry and these integrations together can contribute to the theory and practice of smart sustainable cities.

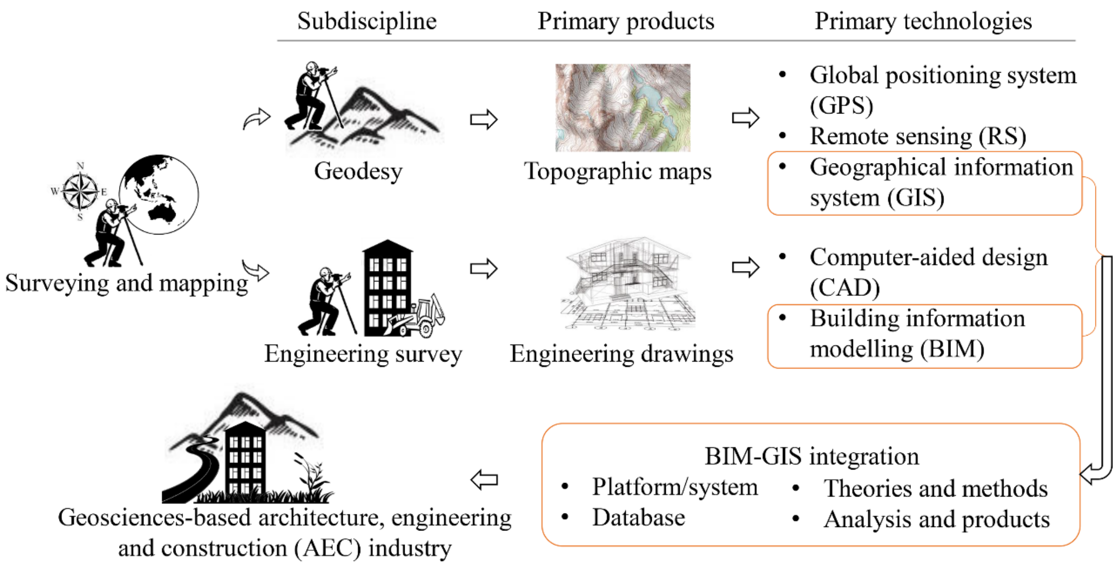

Figure 3-1. History of BIM-GIS integration from the perspective of surveying and mapping.

3.3.3 Comparison of evolution of GIS, BIM and integrated BIM-GIS

Compared with GIS, BIM is still relatively young and primarily serves as a collaborative platform, and more efforts are required to deeply understand and apply BIM in the AEC industry (Wang et al. 2016). Integrated BIM-GIS is in its initial stage and it has rapidly developed in the last three years. In general, both GIS and BIM have experienced six primary evolution stages, including origins, system development, digitalization and visualization, database management, visualization-based analysis and mathematical modelling (Figure 3-2).

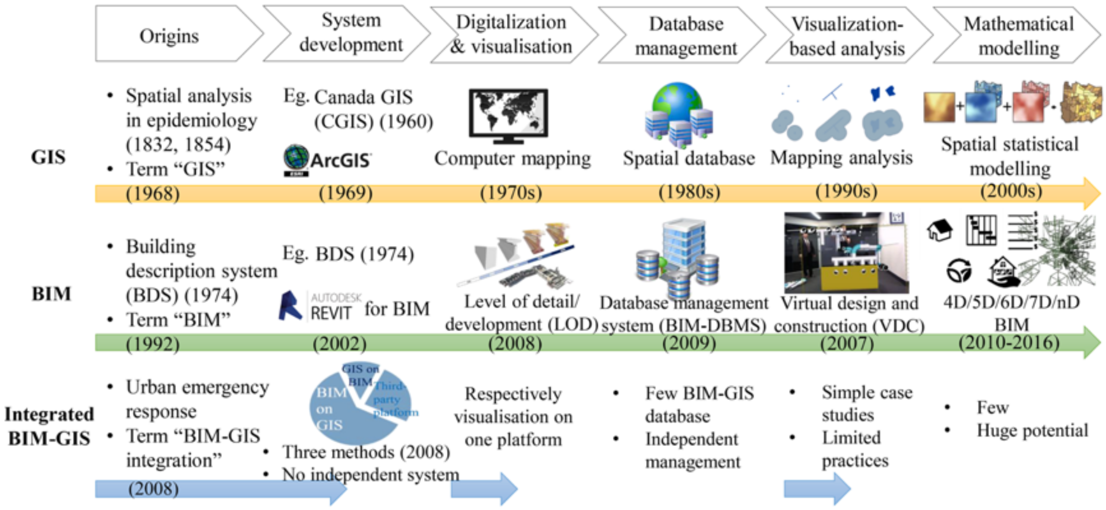

Figure 3-2. Comparison of evolution of GIS, BIM and integrated BIM-GIS

Spatial analysis of patterns and relationships is the central function of GIS (Bailey 1994, Marshall 1991, F Dormann et al. 2007, Wang, Zhang, and Fu 2016, Wang et al. 2012), which was first utilized in the analysis of epidemiology in France and London in the mid-nineteenth century (Rezaeian and Pocock 2012, Jangra et al. 2013, Foster 2013). The term GIS was first used for regional planning by Roger Tomlinson in 1968 (RF 1969, Drummond and French 2008, Ezekwem 2016). The development of computer technology promoted GIS system development, such as Canada GIS (CGSI) for natural resources mapping (Griffith 1980, Fisher 1980) and ArcGIS for commercial applications (Johnston et al. 2001). GIS gradually developed through the computer mapping, spatial database management, visualization-based mapping analysis and spatial statistical modelling from the 1970s to 2000s, and has been widely applied to natural resources, facility management, public health, business and agriculture fields (Berry 1996a). In this thesis, the theories and methods of spatio-temporal data analysis are summarized according to the research and application objectives, as listed in Table 3-2, including the description of spatio-temporal characteristics, exploration of potential factors and spatio-temporal prediction, modelling and simulation of spatio-temporal processes, and spatio-temporal decision making. In this way, researchers and practitioners of the AEC industry can easily access the methods and select proper methods in AEC projects.

Table 3-2. Summary of theories and methods of spatio-temporal data analysis

Research and application objectives	Theories and methods of spatio-temporal data analysis (Wang, Ge, Li, et al. 2014)	Exemplar models
Description of spatio-temporal characteristics	- Spatio-temporal visualization (MacEachren et al. 1999); - Time-series of spatial statistical indicators; - Spatio-temporal indicators that reveal the comprehensive statistics of spatial and temporal variations (Wang, Ge, Li, et al. 2014); - Spatio-temporal clustering and hotspots exploration (Wang, Ge, Li, et al. 2014); - Spatio-temporal interpolation.	- Spatio-temporal scan statistics (Kulldorff 1997); - Self organization mapping (Kohonen 1990); - Spatio-temporal kriging (Cressie and Wikle 2015); - Bayesian maximum entropy (BME) model (Christakos 2000).
Exploration of potential factors and spatio-temporal prediction	Spatio-temporal regression.	- Spatio-temporal multiple linear regression; - Spatio-temporal panel model; - Spatio-temporal Bayes hierarchical model (BHM) (Haining 2003); - Geographically and temporally weighted regression (GTWR) (Huang, Wu, and Barry 2010); - Spatio-temporal generalized additive model (GAM) (Wood 2017).
Modelling and simulation of spatio-temporal process	- Spatio-temporal process modelling; - Spatio-temporal evolution simulation.	- Cellular automation (CA) (Li and Liu 2007); - Geographical agent-based model (ABM) (Lin and Gong 2001); - Computable general equilibrium model (Yong and Jinfeng 2008).
Spatio-temporal decision making	Spatio-temporal decision-making model.	Spatio-temporal multi-criteria decision making (MCDM) (Van Orshoven et al. 2011, Mollalo and Khodabandehloo 2016).

BIM was first known as a building description system for digitization and visualization of building components in 1974 (Eastman et al. 1974). BIM was first termed by Van Nederveen and Tolman in 1992 (Van Nederveen and Tolman 1992), but became popular in the 2000s due to wide commercialization by Autodesk, Bently, Graphisoft, etc (Autodesk 2002, Laiserin 2003). BIM has been fast growing in the past ten years. For digitization and visualization, level of details/development (LoD) is applied in BIM to reflect the progression of the modelling geographic representation from the lowest LoD of general 2D to the highest LoD of BIM involving 3D models and corresponding detailed non-geometric information (Fai and Rafeiro 2014, AIA 2008, Bedrick 2013). BIM database management system (BIM-DBMS) is used for AEC data organization and management, and requires BIM-specific data management practices to ensure efficient applications for teams and projects (Singh, Gu, and Wang 2011, Pavan et al. 2014). BIM-supported virtual design and construction (VDC) is a significant and fast expanding technology for visualization-based analysis and decision-making in the AEC industry (Gilligan and Kunz 2007, Khanzode, Fischer, and Reed 2008). Due to the requirement of applying BIM on mega projects, urban management and other complex situations, multiple dimensions such as time, cost and environmental impacts, are added to 3D BIM for mathematical modelling and analysis. For instance, 4D BIM enables project time allocation and construction sequence scheduling simulations. 5D BIM supports real time cost planning. 6D BIM is used for sustainable element tracking, and 7D BIM can help the life cycle of facility management (Smith 2014, Ikerd 2010). The concept of nD BIM is also proposed to allow all stakeholders to work cohesively and efficiently during the whole project life-cycle, and retrieve and analyse information of scheduling, cost, sustainability, main tenability, stability and safety (Ding, Zhou, and Akinci 2014, Aouad, Lee, and Wu 2005, Lee et al. 2005, Succar 2009).

Analysis of application evolution of integrated BIM-GIS in the AEC industry reveals that BIM-GIS integration is primarily first used for urban emergency simulation, response and management. There are primarily three types of integration methods, extracting BIM data on GIS platforms, extracting GIS data on BIM platforms and using the third-party platforms, where more than half of the researches prefer the first method (Ma and Ren 2017). Even most of the current studies focus on integration technologies, few of them propos an independent system to achieve integrated BIM-GIS. For the digitalization and visualization of integrated BIM-GIS, a mainstream approach is still required to visualize elements on respective BIM or GIS systems. Meanwhile, few studies discuss the issues about BIM-GIS database management and the data sets of BIM and GIS tend to be managed independently. Above discussion also reveals that studies about BIM-GIS integration have rapidly increased since 2015 and tend to have been applied to more complex AEC cases and scenarios in the recent three years. However, there is still a limited number of practical case studies and the integration lacks well supported theories.

A key problem of current BIM-GIS integration is that the integrated BIM-GIS supported analysis and decision making is still in the initial stage. For visualization-based analysis, the advantages of mapping analysis of GIS and VDC of BIM are combined and fully utilized (Figure 3-3), especially the mapping analysis such as spatial proximity analysis, overlay analysis and network analysis. For mathematical modelling, few studies involve both spatial or spatio-temporal statistical modelling of GIS and 4D/nD BIM to address AEC issues. In previous BIM-GIS integration studies, very limited studies utilize spatio-temporal statistical modelling in the applications, even though it is the central function of GIS. Most studies treat GIS as a 3D display platform for geovisualisation of large scale spatial data. However, it should be noted that in the recent twenty years, GIS is generally known as “geographical information science” that covers theories, concepts, methods, systems, database management, applications and decision making (Goodchild 2010). Spatio-temporal statistical modelling is used for accurate modelling of spatial and temporal patterns, exploration of relationships and potential statistical factors, prediction of future distribution scenarios and statistics-based decision making. Therefore, there is great potential for more accurate, deep and flexible application of integrated BIM-GIS and development of its specific theories and methodologies.

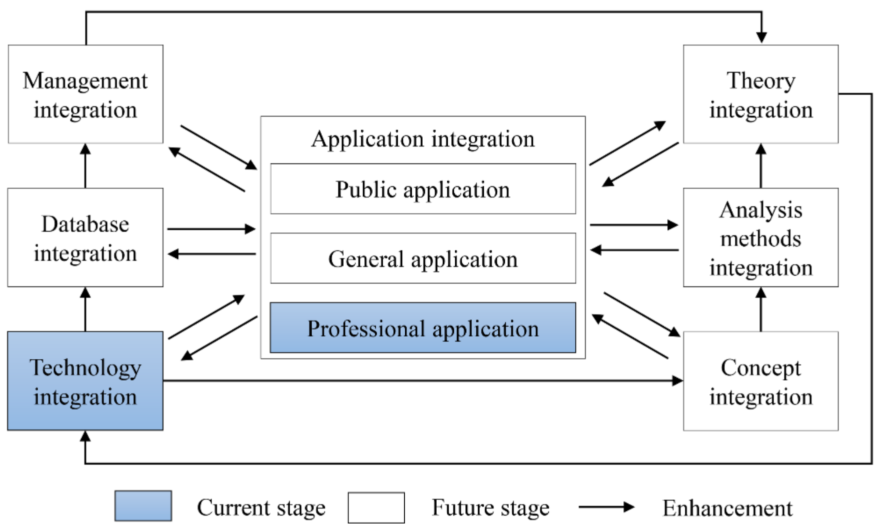

Figure 3-3. Relations among current and future evolution stages of BIM-GIS integration

In addition to the lack of deep analysis and mathematical modelling, there are still massive blanks to be filled for future BIM-GIS integration as shown in Figure 3-3. There are primarily seven stages of BIM-GIS integration, including technology, database, management, concept, analysis methods, theory and application integration. Technology integration means how to integrate both systems from a technological aspect, such as the utilization of IFC and CityGML models. Database integration is to link, interact and merge data from BIM and GIS. Management integration is the collaborative management of respective works, data and information, and systems. Concept integration is to link the terms, definitions, and professional ideas from both fields. Analysis methods integration allows the applications of mutual methods and new methods in the context of the AEC industry. Theory integration is driven by scientific objectives covering technologies, data and information, concepts, methods and management. In the above six integration stages, technology integration of systems can promote the development of concept and database integration. The development of database integration improves management integration. Meanwhile, concept integration promotes analysis methods integration. Both management and analysis methods integration can help the development of theory integration, which in turn can improve the technology integration of systems. In addition, application integration is to apply the above outcomes in the applications, including professional applications of experts, general applications of researchers and practitioners in the AEC industry, and public applications of public participants. The accumulation of applications can also improve the above six integration stages.

BIM-GIS integration is currently at the technology integration and professional application stages. For the technology integration, professional application means that most of the researchers and practitioners of integrated BIM-GIS are experts in the fields of either the AEC industry or geosciences. Few of them are general and public users. The stages of general application and public application is critical for the application of technologies. GIS is utilized by experts, general users in institutes, companies and governments, and public users who can use simple codes or even no code to develop their own tools and address their own problems (Berry 1996a). For instance, Google Maps (https://www.google.com.au/maps) and OpenStreetMap (http://www.openstreetmap.org) enable public users to upload and download their own data and perform simple analysis such as distance measurement, and commercial companies such as Carto (https://carto.com/) and Mapbox (https://www.mapbox.com/) allow public users to generate their own online interactive maps and perform spatial analysis using their own data and GIS methods. With the widespread mobile applications, millions of mobile applications are developed based on Google Maps (https://www.google.com.au/maps) (Lella, Lipsman, and Martin 2015), Gaode Map (http://ditu.amap.com/), Baidu Map (http://map.baidu.com/), etc., for general and public users. Even though BIM is not fully used by public users, a great number of general users such as workers have applied BIM on their practical works in industries (Chai et al. 2017, Wang, Zhang, et al. 2015, Wang, Sun, et al. 2015). Thus, research and practice of GIS and BIM indicate that integrated BIM-GIS can have wide and deep general and public applications in the future. Similar to the application integration, their respective concepts need to be integrated based on the combination of expert knowledge, innovatively integrated database tools and methods, and analysis methods and theories to address BIM-GIS specific smart sustainable city problems.

3.4 Future trends of BIM-GIS integration in AEC industry

Based on the analysis of literature and explanations of BIM-GIS integration evolution progress, this thesis summarizes the future trends of applying BIM-GIS integration in the AEC industry and proposes potential opportunities for BIM-GIS integration from the perspective of spatio-temporal statistical modelling. Three hypotheses for future trends and opportunities of BIM-GIS integration in the AEC industry are proposed, including the technology (loose integration) hypothesis, the science (tight integration) hypothesis and the data source hypothesis as shown in Figure 3-4. The explanations of the hypotheses are presented in Table 3-3 and discussed in the following subsections.

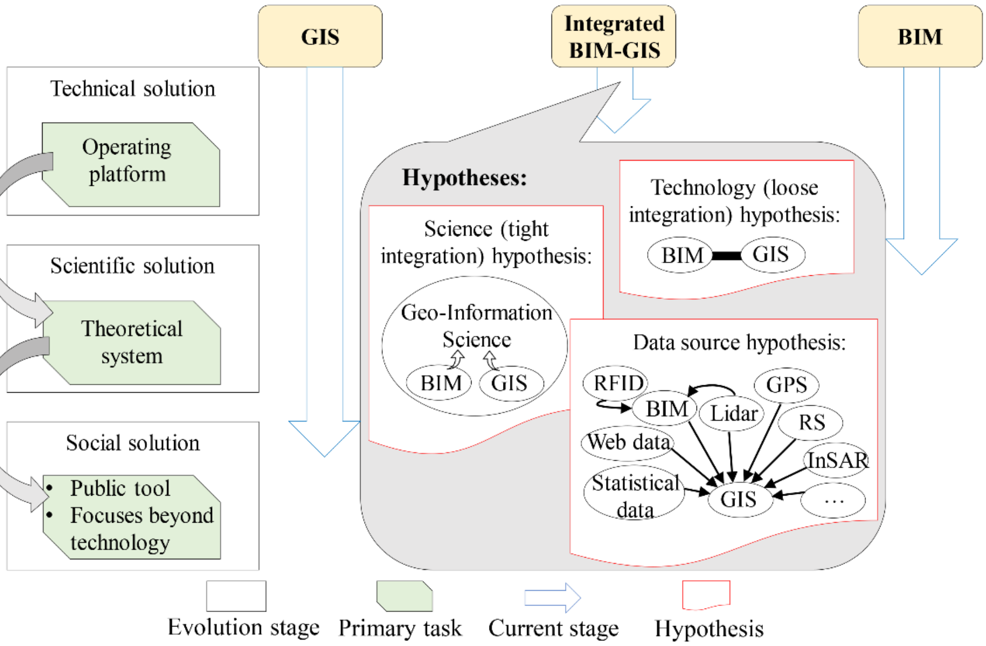

Figure 3-4. Hypotheses of future development of BIM-GIS integration

Table 3-3. Contents of three hypotheses of future trends of BIM-GIS integration

Hypothesis	Content
The technology (loose integration) hypothesis	BIM and GIS are independent systems and areas, and they are partially utilized together to address specific problems.
The science (tight integration) hypothesis	BIM will be developed as building information science for the AEC industry, and then a broader field of geo-information science will cover BIM, GIS and other location-based technologies, services and sciences.
The data source hypothesis	BIM is considered as a data source in the AEC industry for GIS and spatio-temporal statistical analysis.

3.4.1 The technology (loose integration) hypothesis

The technology hypothesis is also named as the loose integration hypothesis, which means BIM and GIS are independent systems and areas, and they are partially utilized together to address specific problems. Most current studies on BIM-GIS integration follow this integration model. The origin of BIM-GIS integration is that to address the AEC issues involving both buildings and its surrounding space, researchers try to combine the respective strong parts of BIM and GIS, especially the detailed representations of physical and functional components of facilities of BIM and spatial 3D models depicting buildings and urban environments of GIS. Integration means extracting data from one system to another or extracting both datasets on a third-party platform for analysis. The difference between future and current integration is that more strengths of BIM and GIS will be explored and used, and spatio-temporal statistics and 4D/nD BIM used for accurate mathematical modelling and analysis. The technology hypothesis has the following advantages:

- This is an easy integration model. There will not be too many changes of future integration methods compared with current ones.
- Concepts, methods, systems, and theories of BIM and GIS will not be changed.
- It is flexible for users. They can choose the integration methods, extracting data from one system to another or using a third-party platform, based on their specific problems to address.

The further development of deeper integration of spatio-temporal statistics and 4D/nD BIM can provide more accurate analysis results, and new sense and knowledge for decision making to satisfy the user requirements of the AEC industry at every stage. The benefits of applying the technology hypothesis of BIM-GIS integration on the AEC industry can be explained by the comparison of using BIM in Table 3-4. Theoretical studies and industrial practices have proved that BIM can significantly improve the performance of both geometric modelling of buildings, infrastructure and cities, and the management of AEC projects (Bryde, Broquetas, and Volm 2013). For instance, most construction projects with the utilization of BIM report cost reduction and effective control.

Table 3-4. Comparison of benefits of BIM and BIM-GIS integration in satisfying the user requirements of AEC industry

User requirements of AEC industry	Benefits of BIM	Benefits of BIM-GIS integration (the technology hypothesis)
Quality management	- Improving design quality by defects detection, eliminating conflicts and decreasing rework; - Ensuring information consistency from design to construction (Chen and Luo 2014).	- Exploring potential factors associated with defects dynamically across whole space during whole construction life-cycle; - Predicting potential spatio-temporal distributions of risks for predictive decision making.
Progress and time management	- BIM-based simulation of construction works enables significant time savings throughout construction period (Bryde, Broquetas, and Volm 2013); - Effective information management and enhanced communication	Construction works could be simulated spatially and temporally for more accurate progress management and time reduction.

	reduces time consumption during information exchange.	
Cost management	Cost reduction and control are the most common benefit from BIM in construction projects (Bryde, Broquetas, and Volm 2013).	Cost is controlled not only seen from the result of construction projects during each stage, but also by the dynamically monitored and analysed spatio-temporal results.
Contract management	BIM enhances contract relationships, and optimizes construction procurement and contract management due to the improvement of execution efficiency of contracts (Olatunji 2014, HE and ZHANG 2016).	Execution and management of contracts are based on the dynamic and predictive decision making.
Health, safety and environment (HSE) management	- Classifying, organizing and integrating fragmented HSE information; - Supporting maintenance by identification, data processing, rule-based decision making, and user interaction (Wetzel and Thabet 2015, Riaz et al. 2014, Zhang et al. 2013, Riaz et al. 2017).	- Spatio-temporal statistical analysis plays more roles in the clustering analysis, correlation analysis, exploration of impacts of potential factors and prediction in HSE management; - A series of new methods can be proposed for the HSE management in AEC industry from the perspective of spatio-temporal statistical analysis by involving the characteristics of AEC projects.
Information management	Effective generation, collection, distribution, storage, retrieval, and disposition of component and project information (Bryde, Broquetas, and Volm 2013).	- More information with large spatial scales is included in the AEC projects, such as the surrounding environment, suppliers far beyond the projects, road network and its geographical and socio-economic factors, and the participants of freight transportation, et al. - Spatio-temporal analysed results and predicted scenarios become one of the primary evidence included in the database for decision making, in addition to the collected and monitored raw data.
Coordination of various sectors	BIM affects project coordination mechanisms in its specific ways and depending on the served purposes, such as a centralized-decentralized structure and a hierarchical-participative decision-making process (Aibinu and Papadonikolaki 2017, Tommelein and Gholami 2012).	Coordination mechanisms are driven by the sense and knowledge sourced from data, information, and their analysis products, which are characterized as spatial and temporal varied, real-time, dynamic, interactive, accurate and practical.

However, there are still challenges of using BIM and some cases show negative benefits during the application, especially the utilization of BIM software and the coordination phase (Bryde, Broquetas, and Volm 2013). Software issues are relatively common in practice since multiple software have to be applied in a project, but they cannot be seamlessly combined due to the difference of software. Therefore, it is a trend to utilize IFC and CityGML models to integrate various functions and avoid detail losses (El-Mekawy, Östman, and Hijazi 2012). This solution also addresses the technical problems of integrating systems of BIM and GIS. In addition, the life cycles of AEC projects are typical spatial and temporal processes, but user requirements during construction cannot be accurately and dynamically described, modelled and managed, due to the lack of comprehensive data-driven spatio-temporal modelling of AEC projects. By involving spatio-temporal statistical analysis, integrated BIM-GIS can more accurately quantify and address these issues.

Compared with BIM, BIM-GIS integration enhanced by spatio-temporal statistics and 4D/nD BIM provides spatial and temporal dynamic and predictive solutions for the user requirements in AEC projects. These solutions are significantly beneficial for satisfying user requirements in quality, progress and time, cost, contract, health, safety and environment (HSE), and information management, and the coordination of various sectors. The spatio-temporal analysed results and predicted scenarios become one of the primary evidence sources included in the database for decision making, in addition to the collected and monitored raw data that is commonly used in current BIM-based solutions. For BIM-GIS integration-based solutions, management methods and coordination mechanisms are driven by the sense and knowledge sourced from data, information, and their analysis products, which are characterized as spatial and temporal varied, real-time, dynamic, interactive, accurate and practical.

3.4.2 The science (tight integration) hypothesis

The science hypothesis, also named the tight integration hypothesis, is a relatively long-term hypothesis. This hypothesis assumes that BIM will be developed as building information science for the AEC industry, and then a broader field of geo-information science will cover BIM, GIS and other location-based technologies, services and sciences. Under this hypothesis, location-based theories and technologies can be tightly integrated by combining their similarities and highlighting strengths. Thus, this hypothesis of BIM-GIS integration primarily relies on the development of BIM. At present, only a few studies consider BIM as building information science for digitization, visualization and analysis of whole project life cycles (Karimi 2013), but it has been a trend of BIM development due to the theoretical needs to manage sophisticated and mega projects in recent years. Correspondingly, new theories and methods will be proposed for the scientific study of analysing user requirements and solutions for the AEC industry by involving the inherent spatio-temporal characteristics of AEC projects. The science hypothesis of BIM-GIS integration provides an opportunity for broadening the scope and comprehensive understanding of the AEC industry and smart sustainable city.

3.4.3 The data source hypothesis

The data source hypothesis considers BIM as a data source in the AEC industry for GIS analysis. Under the data source hypothesis, the role of BIM in the AEC industry is similar to remote sensing (RS) in monitoring natural resources and light detection and ranging (LiDAR) in photogrammetry. Remote sensing is characterized as rapid acquisition, large spatial coverage, and providing access to land, sea and atmospheric data with diverse spatial and temporal resolutions in natural resources monitoring and management (Ge et al. 2016). LiDAR including ground, vehicle, satellite-based and airborne LiDAR can rapidly and accurately measure and analyse dense point clouds without contact with danger and contaminants. Both remote sensing and LiDAR are primarily used as data collection tools, and they can also manage and analyse data, but they are generally combined with GIS to perform complex and comprehensive spatial and temporal analysis to deeply understand the attributes and phenomenon. In addition to remote sensing and LiDAR, there are a series of technologies that have similar roles of data source, such as traditional statistical data, surveying data, web-based data, global positioning system (GPS), and interferometric synthetic aperture radar (InSAR).

Table 3-5 lists the GIS data sources including potential data sources of BIM, and the comparisons of their data examples, general formats, characteristics and application examples. The comparison shows that BIM is a proper data source for buildings and urban infrastructure due to its rich geometric and semantic information, multi-level of detail for various applications and building-level digital representation. In addition, geospatial analysis has been widely employed in the AEC industry including civil engineering and petroleum engineering (Zhou et al. 2007). Meanwhile, BIM can provide diverse data due to different user requirements of AEC projects, quality data, progress and time data, cost data, contract data, and HSE data, et al. For these studies, GIS provides spatial statistical methods for modelling AEC data and problems. Some of the spatio-temporal statistical analysis results also can be regarded as data sources in the form of data and information products. Therefore, the data source hypothesis can enhance GIS applications and promote the strength of BIM for its role in the AEC industry.

Table 3-5. Comparison of GIS data sources

Data source	Data examples	General formats	Characteristics	Application examples
Vector products	- Administrative boundary (Nature Earth 2017); - Spatial data of infrastructure (ArcGIS Hub 2017, Center for International Earth Science Information Network - CIESIN - Columbia University and Information Technology Outreach Services - ITOS - University of Georgia 2013).	.shp	- Relatively low data volume; - Fast display; - Containing attributes information.	- Disease mapping (Kassebaum et al. 2016); - Road and traffic analysis (Cai, Wu, and Cheng 2013, Laurance et al. 2014).
Raster products	- Digital elevation model (DEM) (Tachikawa et al. 2011); - IPCC future climate change scenarios (Moss et al. 2010, Moss et al. 2008, Nakicenovic et al. 2000).	.tif/.img/ Various formats	- Full coverage and spatially continuous; - Good visual effect.	- Gravity modelling (Rexer and Hirt 2014); - Future scenarios prediction (Song et al. 2016, Gao and Bryan 2017).
Surveying data	- Wireless sensor network data (Ge, Liang, et al. 2015, Ge, Wang, et al. 2015, Kang et al.	Table/ Various formats	- Including professional attributes;	- Ecohydrologic al analysis (Ge, Wang, et al. 2015);

		2014, Wang, Ge, Song, et al. 2014); - Air quality ground monitoring data (Ministry of Environmental Protection of the People's Republic of China 2017, Environmental Protection Agency United States 2017).		- Used for specific issues.	- Air quality analysis (Song et al. 2015, Zou et al. 2015);
Statistical data		- Population census data (Australian Bureau of Statitics ABS 2015); - Economic statistical data (Australian Bureau of Statitics ABS 2017).	Table	- Including professional attributes; - Full coverage of a region.	- Urban development (Zhang, He, and Liu 2014); - Tracking migration (Ebenstein and Zhao 2015).
Web data		Location-based social media data	Text/ Various formats	- Current, fine-scaled and rich individual information (Noulas et al. 2011, Andrienko et al. 2013).	- Urban and human mobility studies (Wu, Wang, and Dai 2016).
Global positioning system (GPS) data		- Location data - Ionosphere and troposphere data	ASCII/ Binary/ Text	- Accurate positioning and tracking.	- Trajectory analysis of human and vehicles mobility (Feldt and Schlecht 2016, Siła-Nowicka et al. 2016); - Spatial uncertainty analysis (Wu, Ge, et al. 2015, Ge, Wei, et al. 2017).
Active remote sensing (RS) data	Radar	Meteorological radar	Various formats	- Regardless of weather conditions;	- Flood analysis (Barnolas et al. 2008).

				- Capable in extracting water regions.	
	Light detection and ranging (LiDAR)	Point cloud (ground, vehicle, satellite-based, or airborne)	ASCII/ LAS/ Various formats	- Fast measuring and analysis; - Avoiding contacts with dangers and contaminants; - Accurate distance measurement and dense points.	- Generating accurate 3D models (e.g. DEM and BIM). - Landslide risk assessment (Abdulwahid and Pradhan 2017, Palenzuela et al. 2015, Jebur, Pradhan, and Tehrany 2014).
	Interferometric synthetic aperture radar (InSAR)	- Topography data and ground deformation data	Various formats	- Slight deformation detection; - Large spatial coverage; - Regardless of weather conditions; - Obtaining underground information.	- Ecological analysis (Kıncal et al. 2017); - Ground deformation analysis (Yang, Peng, et al. 2016, Chen, Gong, et al. 2014, Zheng, Fukuyama, and Sanga-Ngoie 2013, Chen et al. 2017).
Passive remote sensing (RS) data	Satellite RS images	- Land surface temperature (NASA 2016a); - Vegetation data (NASA 2016a); - Land cover data (NASA 2016a); - Nighttime lights (The Earth Observation Group 2017).	.tif/ .hdf/ ASCII/Various formats	- rapid acquisition; - Large spatial coverage; - Accessing to land, sea and atmospheric data with diverse spatial and temporal resolutions (Ge et al. 2016).	Vast applications. - Urban studies; - Roads and infrastructures; - Environment.
	Aerial photogrammetry data	- Land cover data;	.tif/ Various formats	- Large spatial coverage;	- 3D analysis (Marzolff and Poesen 2009);

	- Topography data.		- Massive geometric and physical information of features; - Fast mapping.	- Land use analysis (Miyasaka et al. 2016).
Unmanned Aerial Vehicle (UAV) measurements	- Land cover data; - Topography data; - Building data.	.jpg/ Various formats	- Current and fine-scaled information; - High spatial resolution.	- 3D city modelling (GRUEN et al. 2014); - Land use analysis (Hong 2016).
Building information modelling (BIM) data	- Building projects (Lu, Won, and Cheng 2016b, Volk, Stengel, and Schultmann 2014); - Civil infrastructure projects (Cheng, Lu, and Deng 2016).	.ifc/ Various formats	- Rich geometric and semantic information; - Multi-level of details for various applications; - Limited to building-level digital representation.	- Building indoor analysis (Lin et al. 2013); - Mega project application (Cheng et al. 2017, Tan et al. 2017).

3.4.4 BIM-GIS integration for project life cycles

From a spatio-temporal statistical perspective, the three hypotheses of BIM-GIS integration enable more comprehensive applications through the life cycle of AEC projects. Planning and design stages are highly influential in setting the directions for the whole business and project, where BIM-GIS integration not only provides multi-scale and rich geometric and semantic information for the decision makers (Ham et al. 2008), but also evaluates scheduling, cost and sustainability at an early stage in a 3D virtual environment (Cheung et al. 2012). Besides, BIM-GIS integration can also be used to perform complex building performance analysis to ensure optimized building design of both the building and its surrounding space.

During the construction stage, BIM-GIS integration is applied in different aspects that can impact the construction progress. For example, the construction site is the main area on which construction activities are conducted. BIM can provide building information to generate dynamic site layout models (Kumar and Cheng 2015) and GIS can help optimize element distributions (Abune'meh et al. 2016). Safety is another important factor during the construction stage, since accidents during construction cause huge losses of human lives and increase project cost. An approach for safety management to use 4D/nD BIM visualization of construction components (Zhou, Ding, and Chen 2013, Zhang et al. 2015), and spatio-temporal analysis for risk distribution prediction and exploration of contributors. BIM-GIS integration can also be used for project cost control. BIM is used for cash flow and project financing recording during construction (Lu, Won, and Cheng 2016a) and GIS can be applied to spatial and temporal analysis of cost clusters and prediction of cost scenarios.

Operation and maintenance stage is the longest stage of a project life cycle. More than half of previous BIM-GIS integration applications for buildings are in this stage. Under the three hypotheses, the enhanced BIM-GIS integration can address sophisticated problems and provide comprehensive strategies for emergency and disaster simulation, prevention, response and management, heritage protection, mega projects operation, indoor navigation and ecological assessment. Deep application of spatio-temporal statistical modelling and 4D/nD BIM can inspire researchers and practitioners to utilize integrated BIM-GIS to deal with more general AEC issues such as sustainability assessment and asset management. The application objects can be buildings, infrastructures, cities and other larger spatial scale objects.

Demolition is the last stage of a construction project. In this stage, a building or structure is usually deconstructed which generates large amounts of waste materials. BIM is the digital representation of the existing buildings, so it is used for reliable and accurate waste estimation and efficient planning (Hamidi et al. 2014, Cheng and Ma 2013). GIS can help analyse and optimize waste distribution processes, such as optimization of delivery networks, transport services, and environmental assessment. Enhanced BIM-GIS integration can optimize waste reuse and recycling to minimize waste materials, overall energy cost, demolition time and impacts on the surrounding environment.

3.5 Conclusion

With the explosive increase of studies and applications of BIM in recent ten years and BIM-GIS integration in recent three years, utilization of BIM-GIS integration in the AEC industry requires systematic theories beyond integration technologies, and deep applications of mathematical modelling methods, including spatio-temporal statistical modelling in GIS and 4D/nD BIM simulation and management. This thesis reviews previous BIM-GIS integration studies from a spatio-temporal statistical perspective to reveal its evolution and recommend future development trends. Evolution of BIM-GIS integration is characterized by three aspects: application evolution in the AEC industry, history from the perspective of surveying and mapping, and comparison study of evolution of GIS, BIM, and integrated BIM-GIS. Based on the analysis of literature and explanations of evolution progress, this thesis summarizes the future trends of BIM-GIS integration in the AEC industry and proposes potential opportunities of BIM-GIS integration from the perspective of spatio-temporal statistical modelling.

We propose three hypotheses, including the technology hypothesis, the science hypothesis and the data source hypothesis of BIM-GIS integration in the AEC industry for future studies. From the spatio-temporal statistical perspective, the three hypotheses of BIM-GIS integration enable more comprehensive applications through the life cycle of AEC projects. BIM-GIS integration based solutions are significantly beneficial for the management methods and coordination mechanisms, including quality management, progress management and time reduction, cost reduction and control, improvement of health, safety and environment (HSE) performance, information management and the coordination of various sectors. These management methods and coordination mechanisms are driven by the sense and knowledge sourced from data, information, and their analysis products, which are characterized as spatially and temporally varied, real-time, dynamic, interactive, accurate and practical. Therefore, under the proposed hypotheses of BIM-GIS integration, comprehensive data-driven spatio-temporal modelling of AEC projects can provide more accurate and dynamic solutions for quantitative analysis, management and decision making in the future applications to satisfy user requirements of AEC industry.

Chapter 4 Burden of Road Maintenance from Heavy Vehicle Freight Transportation

4.1 Introduction

The study in this chapter employs segment-based ordinary kriging (SOK) and segment-based regression kriging (SRK) for more accurate spatial prediction of traffic volumes of different type of vehicles. SOK and SRK are developed from point-based ordinary kriging (OK) and regression kriging (RK), for traffic data with variable road segment support in the Wheatbelt region of Western Australia (WA). By borrowing ideas from ATAK and top-kriging, SOK and SRK integrate the spatial characteristics of road segments and the spatial homogeneity of each single segment, consider their spatial autocorrelation and enable segment-based data to compute the best linear unbiased estimation. Regression kriging (RK or SRK) is an effective supplement of ordinary kriging (OK or SOK) because it considers the information of covariates to deal with the non-stationarity of random functions (Ge, Liang, et al. 2015). Both segment-based and point-based models are applied for the estimation of diverse types of traffic volumes, including heavy, light or total vehicles. A comparative study of both kinds of models, together with point-based inverse distance weighting (IDW) and universal kriging (UK), and non-spatial linear regression (LR), will give an insight of different traffic behaviours and provide road agencies with proper models that have the best prediction performance. The traffic volumes predicted by segment-based geostatistical models are applied on the assessment of road maintenance burden in the Wheatbelt, WA, which can help provide quantitative and accurate evidence for road asset management. Road maintenance burden is determined by the integration of predicted traffic volumes and restricted access vehicles (RAVs) network based vehicle mass estimation, where RAV network regulates roads that can be accessed by different types of heavy vehicles.

4.2 Methodology

Figure 4-1 shows a schematic overview of predicting traffic volumes with a comparison of segment-based and point-based models. The study process includes data pre-processing, variables selection, performance evaluation with cross validation for different categories of models and traffic volume prediction. As an implementation, the prediction results are applied to evaluate the distribution of road maintenance burden in the Wheatbelt, WA.

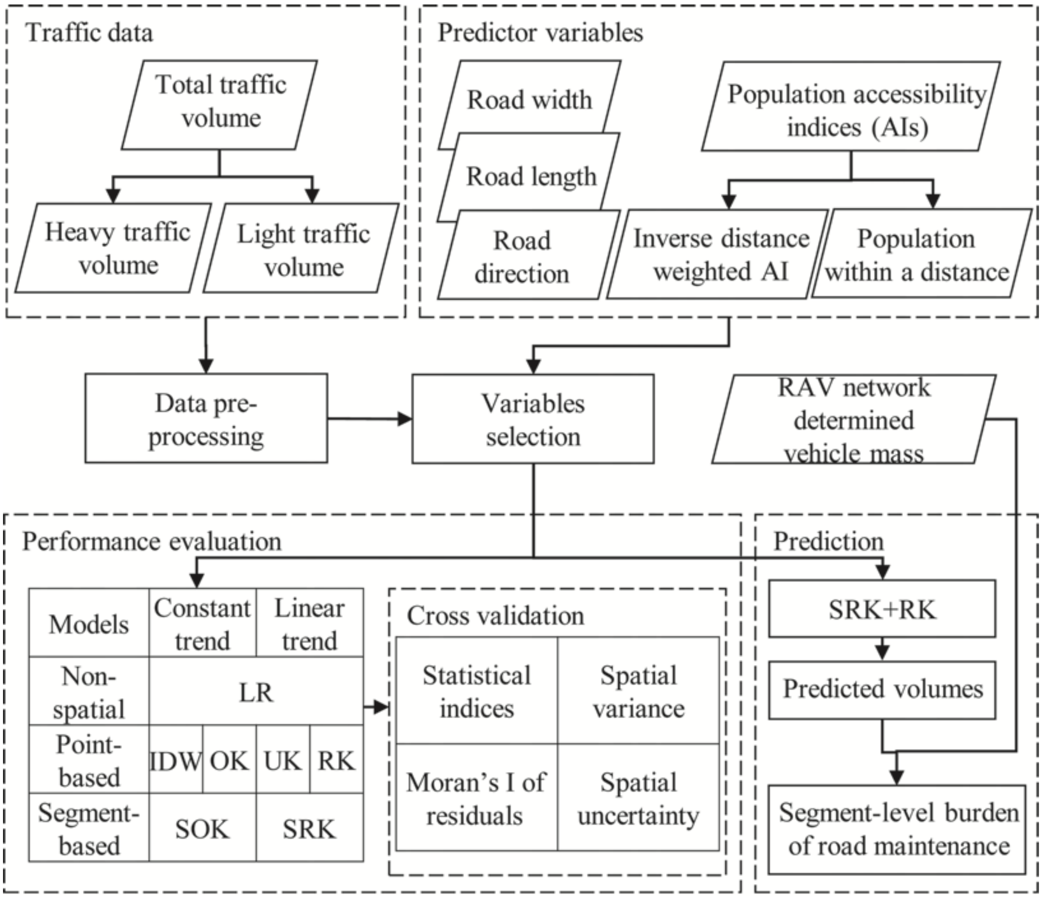

Figure 4-1. Schematic overview of predicting the distribution of road maintenance burden.

4.2.1 Data pre-processing and transformation

For both segment-based and point-based spatial prediction models, the dependent variable is a transformed normally distributed traffic volume of heavy vehicles, light vehicles or total vehicles due to the skewed distributed raw data. Box-Cox transformation is commonly used to remove skewed distributions and ensure stabilizing variations of traffic data (Selby and Kockelman 2013, Lowry 2014). Observed traffic data Y is transformed by the maximum estimation of Box-Cox likelihood function $g_{\lambda}(Y)$ over a power variable λ (Collins 1991, Sakia 1992) and the transformed data Y_t is:

$$Y_t = g_\lambda(Y) = \begin{cases} \frac{1}{\lambda}(Y^\lambda - 1) & \lambda \neq 0 \\ \ln(Y) & \lambda = 0 \end{cases} \quad (4\text{-}1)$$

The maximum likelihood estimations of λ are -0.061, 0.101 and 0.141 for heavy, light and total vehicles respectively. Box-Cox transformation is performed by R *FitAR* package (McLeod et al. 2013).

4.2.2 Variables generation and selection

Widths, lengths and directions of road segments are used as predictor variables for both point-based and segment-based models. Population accessibility indices (AIs) are utilized to depict the accessing population within certain nearby buffer regions of count points or road segments. AIs used in this thesis include the sum of inverse distance weighted population (WAI) within a given distance of count locations or along road segments, and the population within a given distance (DAI) that determines a maximum correlation with traffic volumes. WAI at location or segment u is computed by:

$$WAI_u = \sum_k \frac{Population_k}{d_{uk}^\theta} \quad \forall k, d_{uk} \leq d_{max} \quad (4\text{-}2)$$

where $Population_k$ is the population within buffer region k, d_{uk} is the distance from count location or segment to the buffer region, d_{max} is the maximum band distance (50 km in this thesis) and θ is a power parameter that ensures the maximum correlation between WAI and traffic volumes. Repeated computation of WAI and its correlation with traffic volumes derives that θ equals to 1.4, 1.6 and 1.6 for heavy, light and total vehicles respectively. To determine the distances of DAIs, the correlations between population within 5 km to 50 km (in increments of 5 km) and traffic volumes are computed for both point and segment observations of heavy, light and total vehicles. Results show that maximum correlation for heavy vehicles appears with 50 km buffer regions and that for light and total vehicles with 15 km buffer regions. Step-wise linear regression is used to select predictor variables with significant correlations with traffic volumes and remove insignificantly correlated variables and variables with multicollinearity. Variables selected for predicting heavy vehicle volumes include road segment width, WAI (50 km and $\theta = 1.4$) and DAI (50 km), and those for the volume prediction of light vehicles and total vehicles are road segment width and DAI (15 km).

4.2.3 Segment-based geostatistical modelling

SOK and SRK are proposed to predict traffic volumes at uncounted road segments that are characterized as linear road surfaces with various shapes and lengths. Segment-based geostatistical interpolation is primarily based on **three assumptions.** The **first** assumption is that traffic data are assumed to be spatially homogeneous within a segment, but they are spatially heterogeneous and autocorrelated for different segments. In general, a road segment is the specific representation of a portion of a road with uniform characteristics between two junctions or intersections (Austroads 2016). It is usually defined by a series of rules such as same surface, width, number of lanes, pavement age and traffic conditions (Austroads 2016, Barua, El-Basyouny, and Islam 2016). Based on the above definition of a road segment, traffic behaviours tend to follow similar patterns within a road segment, so it is reasonable to assume the spatial homogeneity of traffic data within a road segment. In addition, the assumption can significantly simplify data analysis and decision making of segment-based traffic issues. Since transport authorities and researchers prefer to monitor traffic data (e.g. annual average daily traffic (AADT)) with the spatial unit of road segment, this assumption also ensures their convenient analysis, management and decision making based on the spatial predictions. **Second**, observed traffic data are regarded as the output of a continuous traffic process across the whole road network. In practice, traffic behaviours among road segments are spatially associated through road network, which means that the traffic data at near road segments are more similar than the data at distant roads segments. **Finally**, spatial stationarity, a general geostatistical assumption, is assumed for segment-based models where the expected variance between observations (or residuals for SRK) is a function of separation distance. SRK is a supplement of SOK by considering the information of covariates to deal with the nonstationary of random functions.

Using SRK to estimate traffic volumes includes **five steps**. The **first step** is modelling trends of traffic data using linear regression where the dependent variables are transformed by Box-Cox function and the selected predictor variables.

The **second step** is to estimate residuals by removing trends in step 1. Based on the assumption of the second-order stationarity of residuals, the segment-based variogram is assessed by maximum likelihood estimation with a great many point values discretised from segments. The covariance calculation between any two segments with discretised points at each segment is shown in the sketch map Figure 4-2. The discretised points are linearly distributed along road segments which are generally several kilometres long and a few metres wide. A variogram is then determined by the parameters of nugget, sill, range and shape. A proper shape is selected from exponential, spherical and Gaussian functions by the comparison of the sum of squared errors (SSE) of model fitness. Thus, the segment covariance $C_s()$ between any two segments s_i and s_j is calculated with the equation

$$C_s(s_i, s_j) = \frac{1}{N(s_i)} \frac{1}{N(s_j)} \sum_{r=1}^{N(s_i)} \sum_{t=1}^{N(s_j)} C(p_r, p_t)$$

$$p_r \in s_i, p_t \in s_j \tag{4-3}$$

where $N()$ is the number of points derived from the discretisation of a segment and p_r and p_t are the discretised points within s_i and s_j.

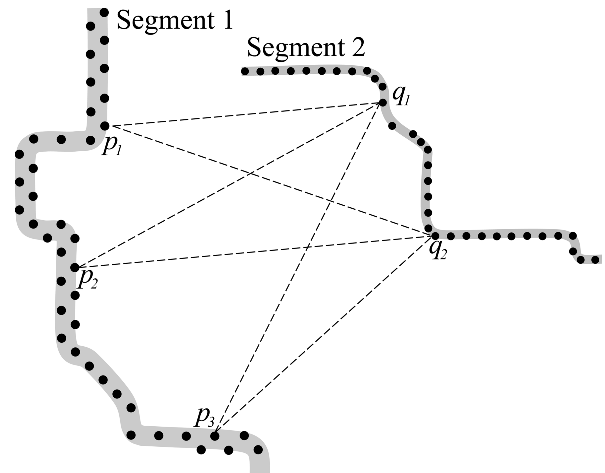

Figure 4-2. Discretisation of two road segments and their covariance with discretised points.

The **third step** is to calculate the estimate and error variance of segment-based residuals. The SRK value $\hat{z}()$ at segment s_0 where traffic volumes are not counted is estimated by a linear combination of m neighbouring segments under the assumption of the second-order stationarity of residuals by the equation

$$\hat{z}(s_0) = \sum_{i=1}^{m} \omega_i(s_0) z(s_i) \tag{4-4}$$

where s_i is the road segment over which traffic volumes are counted, and $\omega_i(s_0)$ is the weight for $z(s_i)$ at segment s_0. The weights are estimated by

$$\begin{cases} \sum_{j=1}^{m} \omega_j(s_0) C_s(s_i, s_j) + \mu(s_0) = C_s(s_0, s_i), \; i = 1,2,\dots,m \\ \sum_{j=1}^{m} \omega_j(s_0) = 1 \end{cases} \tag{4-5}$$

and the corresponding error variance of SRK estimation at line s_0 is calculated with the equation

$$\hat{\sigma}^2(s_0) = C_s(s_0, s_0) - \sum_{i=1}^{m} \omega_i(s_0) C(s_0, s_i) - \mu(s_0) \tag{4-6}$$

The **fourth step** is to generate the estimated traffic volumes by adding SRK estimates to their trends. The **last step** is using cross validation to validate the model performance of SRK by comparing with SOK and point-based interpolation methods, IDW, OK, UK and RK. Point-based interpolations are modelled by R *automap* and *gstat* packages, and segment-based models are done by R *rtop* package.

4.2.4 Integration of segment-based and point-based predictions

The inverse-variance weighting method is used for the integration of both SRK and RK derived results due to their respective contributions on diverse traffic behaviours. The inverse-variance weighted average traffic volume $\hat{Y}_{integ}$ and its least estimation variance $\hat{\sigma}_{integ}^2$ are

$$\hat{Y}_{integ} = \frac{\sum_{\tau=1}^{T} \frac{\hat{Y}_\tau}{\sigma_\tau^2}}{\sum_{\tau=1}^{T} \frac{1}{\sigma_\tau^2}} \tag{4-7}$$

$$\hat{\sigma}_{integ}^2 = \frac{1}{\sum_{\tau=1}^{T} \frac{1}{\sigma_\tau^2}} \tag{4-8}$$

where $\hat{Y}_\tau$ and σ_τ^2 are the estimate and variance of model τ ($\tau = 1, \dots, T$). In this case, predictions and their kriging estimation variance of SRK and RK models are integrated for their combined predictions.

4.2.5 Performance comparison between segment-based and point-based models

To compare the prediction accuracy of different spatial prediction models, three statistical indices are used for prediction accuracy evaluation in the cross validation, including mean error (ME), mean absolute percentage error (MAPE) and the coefficient of determination (R^2). The coefficient of determination stresses the fitness of different spatial prediction models, and the mean error and mean absolute percentage error are used to highlight the prediction errors of different models. Their respective equations are:

$$\mathrm{ME} = \frac{1}{n}\sum_{\kappa=1}^{n}(O_\kappa - P_\kappa) \tag{4-9}$$

$$\mathrm{MAPE} = \frac{100}{n}\sum_{\kappa=1}^{n}\left|\frac{O_\kappa - P_\kappa}{O_\kappa}\right| \tag{4-10}$$

$$R^2 = \frac{\left(\sum_{\kappa=1}^{n}(O_\kappa - \bar{O})(P_\kappa - \bar{P})\right)^2}{\sum_{\kappa=1}^{n}(O_\kappa - \bar{O})^2 \sum_{\kappa=1}^{n}(P_\kappa - \bar{P})^2} \tag{4-11}$$

The mean estimation variance and estimated uncertainty of geostatistical models (OK, SOK, UK, RK and SRK) are also computed to compare the improvement of segment-based models with that of point-based models. Wherein, the inverse Box-Cox transformation of traffic volume $\hat{Y}$ is:

$$\hat{Y} = G_\lambda(\hat{Y}_t) = \begin{cases} (\hat{Y}_t\lambda + 1)^{\frac{1}{\lambda}} & \lambda \neq 0 \\ e^{\hat{Y}_t} & \lambda = 0 \end{cases} \tag{4-12}$$

where $\hat{Y}_t$ is the predicted transformed data and $G_\lambda(\hat{Y}_t)$ is the inverse transformation function. Thus, its estimated standard deviation $\sigma_{\hat{Y}}$ is:

$$\sigma_{\hat{Y}} = \sqrt{\left(\frac{\partial G_\lambda(\hat{Y}_t)}{\partial \hat{Y}_t}\right)^2 \sigma_{\hat{Y}_t}^2} = \frac{\partial G_\lambda(\hat{Y}_t)}{\partial \hat{Y}_t}\sigma_{\hat{Y}_t} = \begin{cases} (\hat{Y}_t\lambda + 1)^{\frac{1-\lambda}{\lambda}}\sigma_{\hat{Y}_t} & \lambda \neq 0 \\ e^{\hat{Y}_t}\sigma_{\hat{Y}_t} & \lambda = 0 \end{cases} \tag{4-13}$$

where $\sigma_{\hat{Y}_t}$ is the standard deviation estimation of $\hat{Y}_t$, and corresponding kriging estimation uncertainty is computed by:

$$\mu_{\hat{Y}} = \frac{\sigma_{\hat{Y}}}{\hat{Y}} \tag{4-14}$$

Further, the estimated volume of total vehicles $\hat{Y}_{total}$ is that of heavy vehicles $\hat{Y}_{heavy}$ plus that of light vehicles $\hat{Y}_{light}$, so the estimated standard deviation $\sigma_{\hat{Y}_{total}}$ and estimation uncertainty $\mu_{\hat{Y}_{total}}$ of total vehicle are:

$$\sigma_{\hat{Y}_{total}} = \sqrt{\sigma_{\hat{Y}_{heavy}}^2 + \sigma_{\hat{Y}_{light}}^2} \tag{4-15}$$

$$\mu_{\hat{Y}_{total}} = \frac{\sigma_{\hat{Y}_{total}}}{\hat{Y}_{total}} \tag{4-16}$$

4.2.6 Estimation of road maintenance burden

In this step, segment-based prediction of traffic volumes is implemented on the estimation of road maintenance burden with the RAV network based vehicle mass estimation in the Wheatbelt, WA.

4.3 Study area and data

The Wheatbelt is one of the most important grain production regions in WA, Australia (Figure 4-3). Heavy vehicles are a primary tool for the transportation of grain and industrial production. In the Wheatbelt, there are 280 primary segments of main roads distributed within the road networks by RAV network. Regional areas and Perth, the capital of WA, are linked by six major roads running through the Wheatbelt, including Brand Highway, Great Northern Highway, Great Eastern Highway, Brookton Highway, Great Southern Highway and Albany Highway. The classification of RAV networks is based on axles of heavy vehicles, and lists the mass of heavy vehicles in each category (Main Roads Western Australia 2016a). The total number of heavy vehicles accounts for about twenty percent of all vehicles, however, their impact on road damage is much greater than light vehicles. Heavy vehicles are primarily used for freight transportation and are characterized by large maximum permitted mass ranging from 42.5 t to 147.5 t (Main Roads Western Australia 2016a).On the other hand, the weight of a standard light vehicle is only 1.65 t and the gross vehicle mass (GVM) is not allowed to exceed 4.5 t in Australia (Department of Transport - The Government of Western Australia 2016). Volume of heavy vehicles and light vehicles have been collected annually by Main Roads Western Australia, from fiscal years of 2008/2009 to 2013/2014 at 627 counting locations on 148 road segments distributed in the Wheatbelt (Main Roads Western Australia 2015). This means that traffic volumes on about half of the road segments on main roads are counted, and the other half of road segments are not counted, even though they are also very important RAV networks. The counted volumes are summarized at segment level for spatial and temporal consistency. The mean summarized segment-level observations of heavy, light and total vehicle volumes are 194.2, 809.2 and 1003.4 vehicles/(km·day), respectively.

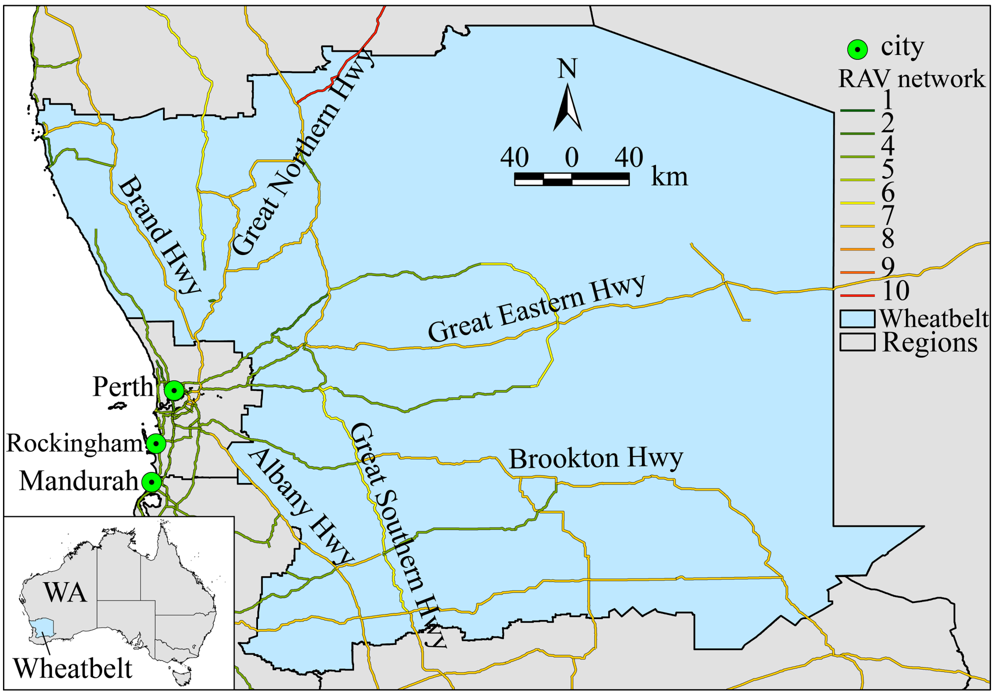

Figure 4-3. Main roads and categories of RAV network in Wheatbelt, WA, Australia.

In addition, predictor variables are used to model trends for kriging-based models with regression. The predictor variables collected include width (m), length (km) and direction of road segments (from east-west direction (0) to north-south direction (1)) and AIs, including WAI and DAI. Population is an effective indicator for traffic prediction since a dense traffic volume usually reveals dense human activities (Dong et al. 2016). Population data of raster type with a spatial resolution of 1 km is obtained from NASA Socioeconomic Data and Applications Center (SEDAC) (Center for International Earth Science Information Network - CIESIN - Columbia University 2016).

4.4 Experiments and Results

4.4.1 Segment-based models for traffic prediction

The SRK variograms for heavy and light vehicle interpolations are computed respectively (Fig 4-4). It illustrates the sample variograms and semivariogram functions of distance and spatial geometry, where solid lines represent semivariogram functions of equally sized segments and dotted ones are functions of the combination of various segments. The spatial characteristics of road segments are described by the multiplication of segment length and width. The segment-based variograms are a series of functions of distance and combined spatial geometry, and their shapes are significantly different to point-based fitted variograms (dark line). Shape distinction in the variograms of SRK for heavy vehicles is larger than that of SRK for light vehicles.

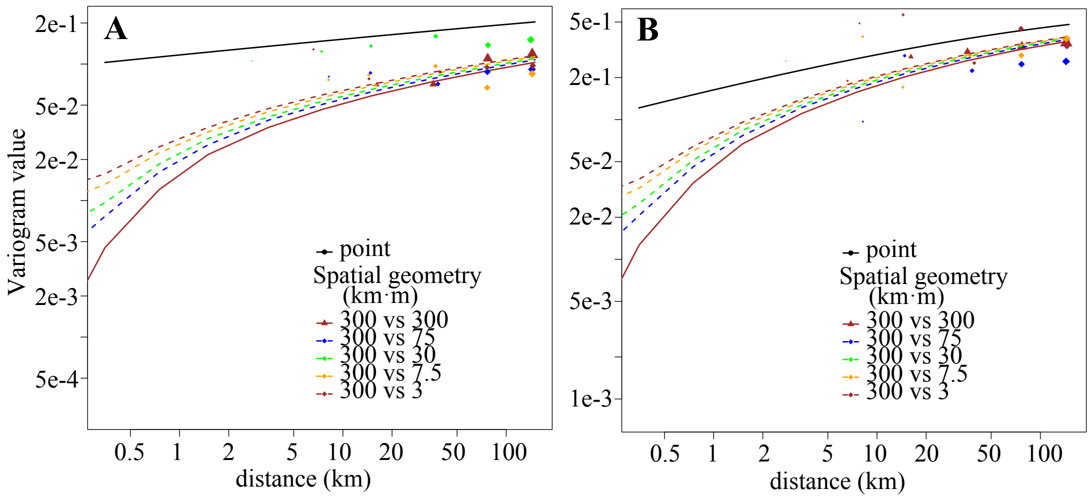

Figure 4-4. Sample and fitted variograms of SRK model for heavy vehicle (A) and light vehicle (B) predictions.

4.4.2 Performance comparison for segment-based, point-based and non-spatial models

Ten-fold cross validations are utilized to assess model performance with the statistical indices ME, MAPE and R^2. The statistical summary of cross validation is listed in Table 4-1. For interpolation models without regression, prediction errors (ME and MAPE) are significantly reduced by SOK compared with IDW and OK. The performance of models with regressions is generally improved compared with pure spatial interpolations such OK (Zou et al. 2015). SRK performs better for predicting heavy vehicle volumes (ME = 8.5; MAPE = 25.0%) than non-spatial and point-based models, including UK (ME = 16.1; MAPE = 28.0%), RK (ME = 17.1; MAPE = 27.4%) and LR (ME = 17.3; MAPE = 27.4%). However, SRK with ME of 21.1 and MAPE of 22.2% is weaker than RK (ME = 13.2; MAPE = 20.8%) for the prediction of light vehicle volumes. The integration of SRK for heavy vehicles and RK for light vehicles (SRK+RK) predicts total vehicle volumes with the smallest prediction errors of ME (21.7) and MAPE (18.8%) compared with those of pure point-based RK (ME =30.4; MAPE=19.2%), pure segment-based model SRK (ME = 29. 6; MAPE = 20.1%), and the model without the differentiation of two types of vehicles (SRK(all)) (ME = 24.5; MAPE = 20.0%). In addition, the coefficient of determination R^2 also proves that SRK with R^2 = 0.677 fits better than other models for heavy vehicles, but RK with R^2 = 0.763 fits better than SRK with R^2 = 0.606 for light vehicles. In total, cross validation R^2 of SRK+RK is 0.805, which is higher than pure SRK but slightly weaker than the pure RK model due to the imbalance of vehicle volumes (i.e. the average number of light vehicles is four times as many as that of heavy vehicles).

Table 4-1. Statistical summary for cross validation of segment-based, point-based, and non-spatial models

Vehicle	Model	Mean	ME	MAPE	R^2	Mean variance
Heavy vehicles	IDW	154.5	39.712	0.392	0.538	/
	OK	153.5	40.780	0.367	0.579	5.224E+05
	SOK	169.4	**24.803**	**0.366**	**0.564**	1.301E+05
	LR	178.1	16.117	0.280	0.634	/
	UK	176.6	17.658	0.274	0.666	2.224E+05
	RK	177.0	17.279	0.274	0.654	2.265E+05
	SRK	185.7	**8.499**	**0.250**	**0.677**	4.941E+04
Light vehicles	IDW	751.4	57.756	0.458	0.424	/
	OK	661.3	147.859	0.423	0.274	1.812E+08
	SOK	767.9	**41.253**	**0.382**	**0.431**	2.603E+07
	LR	778.7	30.438	0.212	0.758	/
	UK	778.0	31.193	0.208	0.753	8.493E+07
	RK	796.0	**13.151**	**0.208**	**0.763**	8.205E+07
	SRK	788.1	21.109	0.222	0.606	5.312E+06
Total vehicles (heavy plus light vehicles)	IDW	905.9	97.468	0.423	0.452	/
	OK	814.8	188.638	0.396	0.350	1.818E+08
	SOK	937.4	**66.055**	**0.360**	**0.470**	2.624E+07
	LR	956.9	46.555	0.193	0.805	/
	UK	954.6	48.851	0.193	0.801	8.516E+07
	RK	973.0	30.430	0.192	0.811	8.232E+07
	SRK	973.8	29.608	0.201	0.685	5.381E+06
	SRK+RK	981.8	**21.650**	**0.188**	**0.805**	8.209E+07
	SRK(all)	978.9	24.525	0.200	0.686	/

Cross validation results indicate that the prediction performance of SRK is associated with the relationship between the spatial heterogeneity and spatial geometry of spatial segment-based data. According to the characteristics of road segments mentioned above, short roads tend to be distributed in urban and densely populated areas, such as towns, but long roads are primarily distributed in rural and regional areas, where heavy vehicle freight transportation is more frequent than in populated areas. This phenomenon enables SRK to predict segment-based traffic volumes of heavy vehicles better than those of light vehicles, since SRK characterizes the spatial geometry of road segments to predict traffic volumes, and the spatial geometry of long roads is more distinct than short roads compared with point-based observations. Due to the consideration of spatial geometry of road segments, spatial autocorrelations will be different between point-based and segment-based observations. In this thesis, the spatial local autocorrelations are presented by local indicators of spatial association (LISA) (Anselin 1995). The spatially significant autocorrelated roads are expressed by four groups, including high-volume roads and neighbours (H-H), low-volume roads and neighbours (L-L), low-volume roads and high-volume neighbours (L-H), and high-volume roads and low-volume neighbours (H-L) (Ge, Song, et al. 2017). Figure 4-5 (A-D) shows the spatial autocorrelations of point-based and segment-based observations of heavy vehicles and light vehicles respectively. Figure 4-5 (E and F) compares the spatial geometry of roads with significant spatial autocorrelations between point-based and segment-based traffic volumes. Since the numbers of roads with significant spatial autocorrelations are different for point-based and segment-based data, the spatial geometry is summarized with mean and standard deviation between ten-quantile values. Schematic diagrams are added to explain the results. Results show that for the spatially significant autocorrelated volumes of all heavy vehicles, spatial geometry of roads with segment-based observations is larger than that with point-based observations, which means relatively long roads tend to be locally clustered and serve the heavy vehicles. While, when involving spatial geometry, volumes of light vehicles on short roads are significantly clustered, but the local autocorrelations of light vehicles on relatively long roads will be reduced. This result reveals that SRK can improve prediction accuracy for segment-based spatial data whose spatial autocorrelation is significant in segments with large spatial geometry than that in the segments with small spatial geometry. Thus, the SRK model relies on both significant spatial heterogeneity of segment-based data and relatively large spatial geometry of segments.

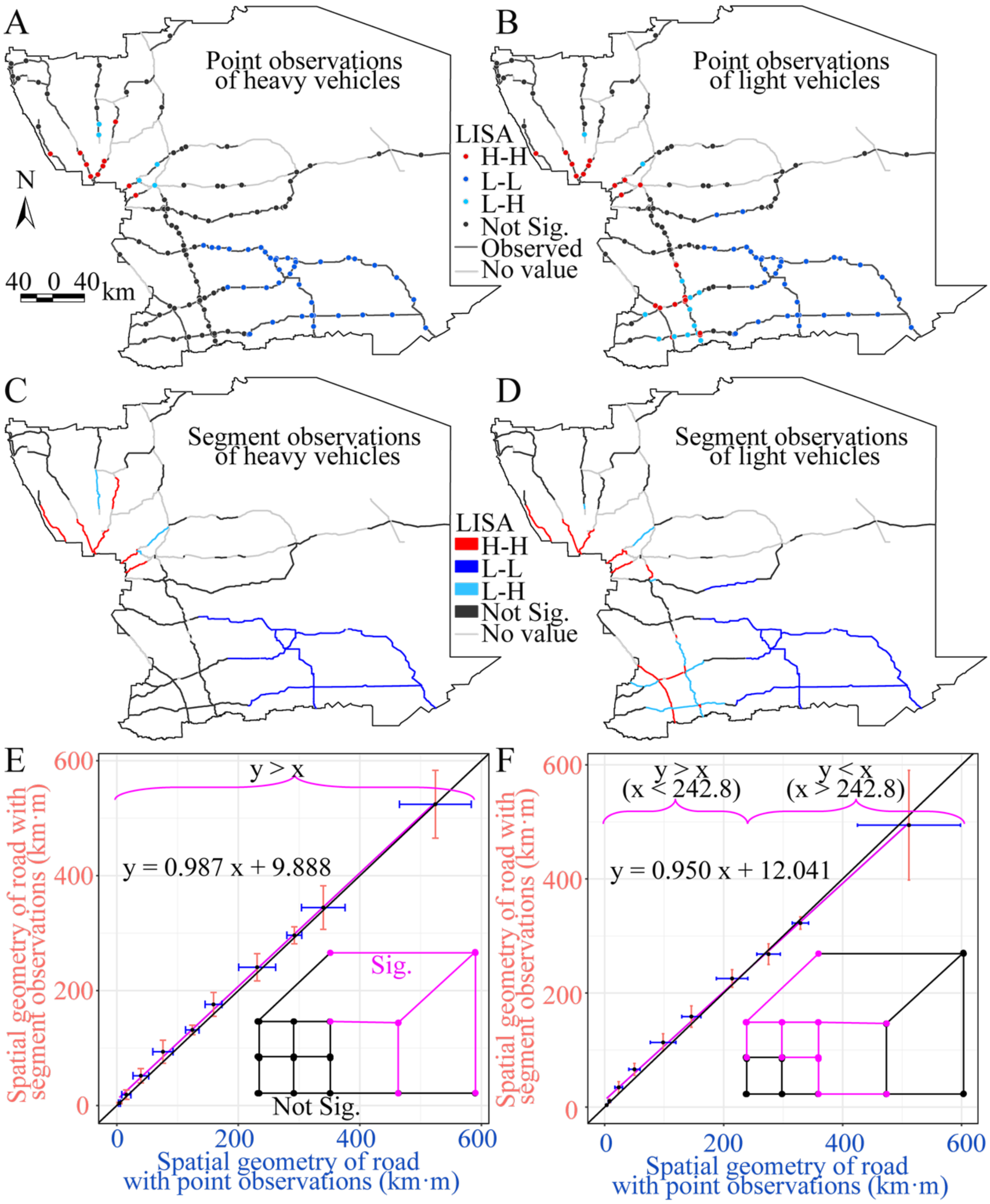

Figure 4-5. Spatial geometry comparison (E: heavy vehicles; F: light vehicles) between roads with significantly local autocorrelated point-based (A: heavy vehicles; B: light vehicles) and roads with segment-based observations (C: heavy vehicles; D: light vehicles).

Figure 4-6 presents the results from the ten-fold cross validations performed for the predictions of heavy, light and total vehicle volumes on road segments respectively. Scatter plots and simple linear regressions are used to present the relationships between traffic volume observations and predictions from point-based models OK and RK, and segment-based models SOK and SRK, together with the combination of SRK for heavy vehicles and RK for light vehicles for the prediction of total vehicles. Results show that SRK and RK can better predict heavy and light vehicle volumes respectively, and SRK+RK is the best prediction model for total vehicle volumes.

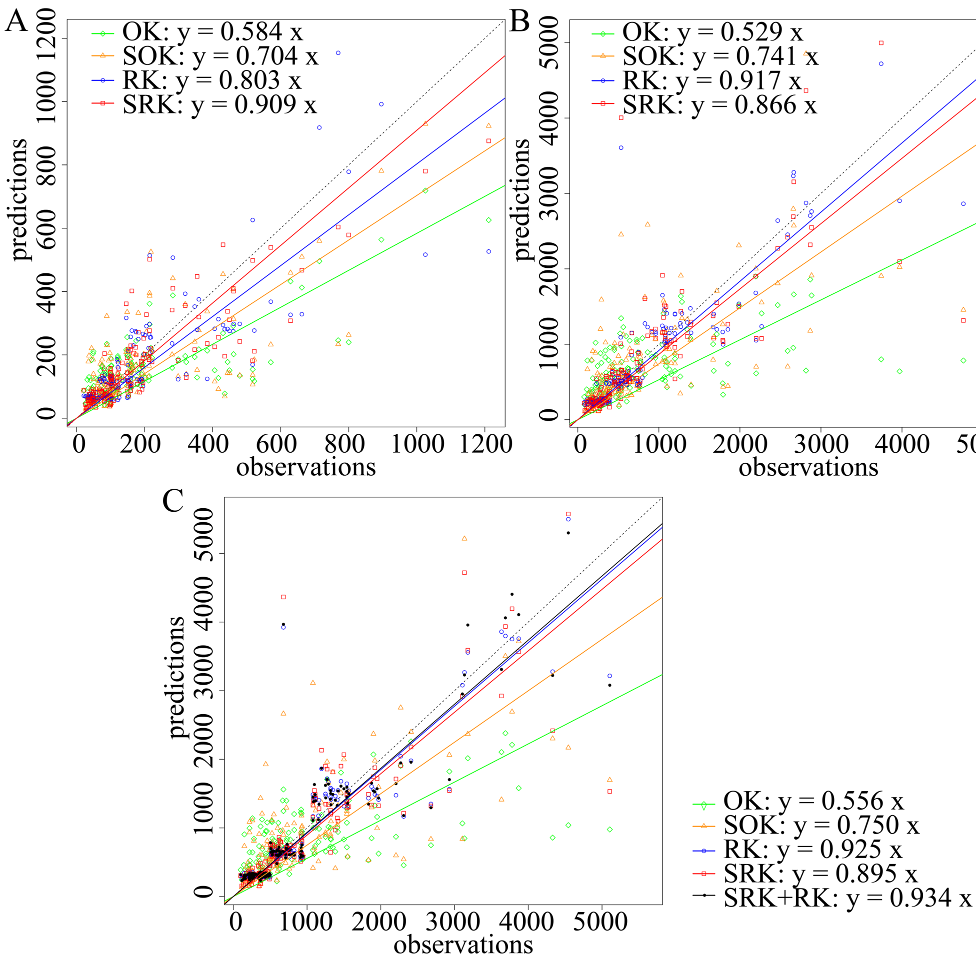

Figure 4-6. Comparison of observations and cross-validation predictions from geostatistical segment-based and point-based models for heavy traffic volume (A), light vehicle volume (B) and total volume (C).

Spatial autocorrelation of residuals reveals the fitting improvement of models. Moran's I is used to describe spatial autocorrection with a more significant spatial autocorrelation showing large absolute values of I and Z. For models without regression, spatial autocorrelation of SOK fitted residuals is Moran's I = 0.007, pseudo p = 0.331 and Z value = 0.383 for heavy vehicles and Moran's I = 0.041, pseudo p =

0.074 and Z value = 1.472 for light vehicles, and that of OK fitted residuals is Moran's I = -0.044, pseudo p = 0.104 and Z value = -1.116 for heavy vehicles and Moran's I = 0.044, pseudo p = 0.070 and Z value = 1.557 for light vehicles. This result shows that SOK reduces more spatial autocorrelations compared with OK for heavy vehicles but the reduction for light vehicles is slight. For kriging models with regression, spatial autocorrelation is reduced by SRK (Moran's I = -0.034, pseudo p = 0.183, Z value = -0.767) compared with RK (Moran's I = 0.098, pseudo p = 0.012, Z value = 3.109) for the prediction of heavy vehicles. In contrast, it is not reduced by SRK (Moran's I = -0.041, pseudo p = 0.098, Z value = -1.090) for predicting light vehicle volumes comparing to RK (Moran's I = -0.026, pseudo p = 0.234, Z value = -0.624). This result demonstrates that the traveling behaviours of heavy vehicles are more related with the spatial characteristics of road segments and segment-based models are more advantageous for explaining these characteristics. On the other hand, the traveling behaviours of light vehicles are different as they tend to have limited relationship with spatial geometry of segments and it is better to directly use a point-based model for their prediction.

Table 4-1 and Figure 4-7 also illustrate the comparison of model performance from the perspective of kriging standard deviation and estimation uncertainty. Standard deviation is the squared root of spatial variance, and the estimated uncertainty is computed as kriging standard deviation divided by the prediction value (Skøien et al. 2014). Results show that the improvements of standard deviation of segment-based models, SOK and SRK, over point-based models, OK, UK and RK, are apparent. For the prediction of heavy vehicles, 78.19% of spatial variance and 69.03% of standard deviation are improved by SRK on average compared with RK, the best performing point-based model. It is also demonstrated that the fitting improvement of segment-based models primarily comes from the reduction of estimated standard deviation. Figure 4-7(A) shows the relationships between residuals and standard deviation. It presents that most of the fitting residuals are located within three times the estimated standard deviation (grey curve) and two times the estimated standard deviation (black curve), and segments with small standard deviations generally have relatively small fitting residuals. Segment-based models have both lower residuals and standard deviations than point-based models. Figure 4-7(B) illustrates a comparison of the standard deviations among segment-based and point-based models. Segment-based models, especially SRK, have much higher cumulative density at low standard deviations.

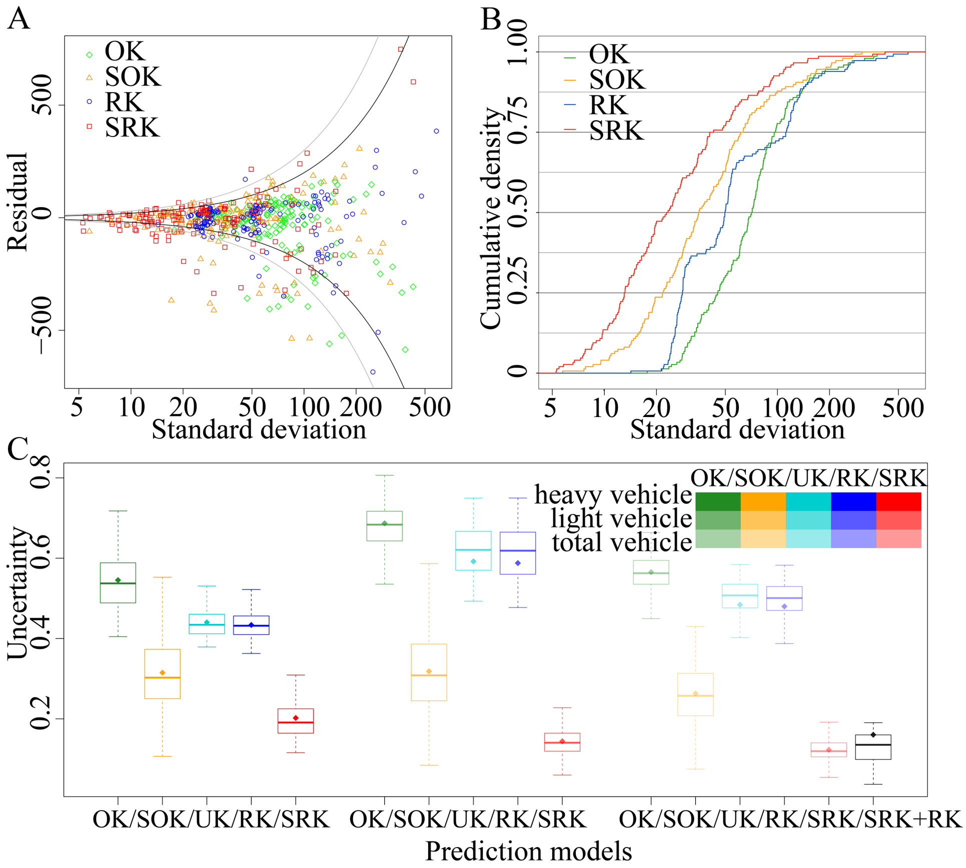

Figure 4-7. Standard deviation and uncertainty summaries of predicted errors for geostatistical segment-based and point-based models. Relationship between residuals and standard deviation (A), cumulative possibility density of standard deviation (B) and estimated uncertainty summary (C).

Figure 4-7 (C) shows the statistical summary of estimated uncertainty. It shows that regression and segment-based models both run well on reducing estimated uncertainty and the reduction from segment-based models is apparent. On average, 53.36% of estimated uncertainty is improved by SRK for heavy vehicles compared with RK. The uncertainty of the SRK+RK model with an average value of 0.160 is slightly higher than the pure SRK model due to the integration of the RK-based prediction for light vehicles whose estimated uncertainty is high, but it is still much lower than the uncertainty of purely point-based models, including UK and RK with average values of 0.484 and 0.470. Thus, the improvement of estimated uncertainty from the SRK+RK model is 65.96% compared with the point-based RK model.

4.4.3 Spatial prediction of heavy and light vehicle volumes

Figure 4-8 shows the maps of predicted traffic volumes for heavy, light and total vehicles with the observations plotted at the middle points of road segments, and spatial distributions of respective prediction uncertainty. The mean predictions of heavy, light and total vehicle volumes are 277.4, 1006.0 and 1283.4 vehicles/(km·day), and the maximum volumes are 1172.0, 3547.0 and 4719.0 vehicles/(km·day) respectively. The corresponding distributions of kriging prediction uncertainty calculated by equation (4-14) and (4-16) are also displayed on the maps. Uncertainty of SRK-based heavy vehicle prediction model ranges from 0.13 to 0.43. Uncertainty of RK-based light vehicle prediction model ranges from 0.45 to 0.65, and uncertainty of SRK+RK-based total vehicle prediction model ranges from 0.30 to 0.58.

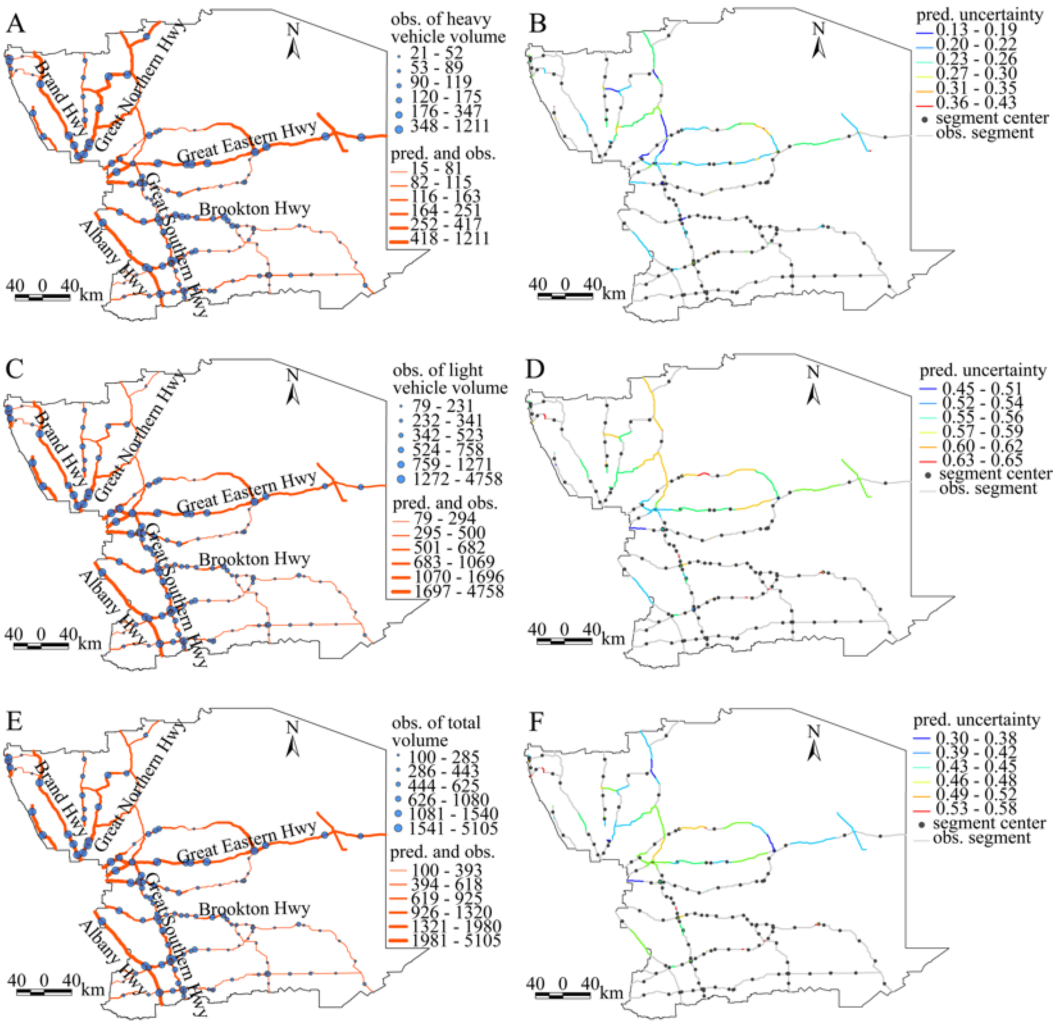

Figure 4-8. Predictions of traffic volumes (heavy vehicle volume: A; light vehicle volume: B; total volume C) and corresponding prediction uncertainty (heavy vehicle volume: D; light vehicle volume: E; total volume F), where points are observations and lines indicate predictions.

4.5 Discussion

This study proposes segment-based models, SOK and SRK, for integrating spatial characteristics and spatial homogeneity of road segments with geostatistical interpolation methods to more accurately predict traffic volumes. Results show that segment-based models can reduce prediction errors compared with point-based models by the consideration of spatial geometry of road segments, and reduce prediction standard deviation and uncertainty. Segment-based models also can better explain spatial autocorrelation of residuals through involving spatial geometry information of segments in kriging models with segment-based covariance and semivariogram functions. SRK performs much better than point-based models for the prediction of heavy vehicles, because the traveling behaviours of heave vehicles are more relevant when spatial characteristics of road segments are included. In the Wheatbelt, heavy vehicles primarily run on main roads and are used for long-distance freight transportation between grain production areas and densely populated regions located in the west of the Wheatbelt, such as Perth (capital city) and Fremantle Port. In contrast, RK is a better model for the prediction of light vehicle volumes than SRK. This phenomenon can be explained by the characteristics of the SRK model that spatial geometry of segments is considered for prediction. SRK can improve prediction accuracy for segment-based spatial data whose spatial autocorrelation is higher in segments with large spatial geometry than that in the segments with small spatial geometry. Thus, we recommend that the relationship between spatial geometry of segments and the spatial heterogeneity of segment-based data should be examined before SRK modelling. A combination of SRK for heavy vehicles and RK for light vehicles is adopted for traffic volume prediction. Results reveal that the combined SRK+RK method has advantages on the prediction of both heavy and light vehicles with high prediction accuracy.

The SRK+RK-based predictions of traffic volumes are applied on the estimation of road maintenance burden in the Wheatbelt, WA. Road maintenance burden at segment level is estimated by the integration of the traffic volume predictions and the RAV network determined vehicle mass limitations. The distributions of the estimated ranges of vehicle masses for heavy, light and total vehicles are calculated at all segments, together with the statistical summaries shown in Figure 4-9. The minimum masses of vehicles shown in the maps are conservative estimates, which assume that loads of all vehicles are restricted within the minimum limitations of the RAV network. On main roads in the Wheatbelt, the average masses of heavy, light and total vehicles are [22.49, 22.69], [1.56, 4.26] and [24.05, 26.95] thousand tons per kilometre per day, and their total masses are [82.78, 83.88], [4.64, 12.66] and [87.42, 96.54] million tons per day. The road maintenance burden from the mass of heavy vehicles is much bigger than that of light vehicles.

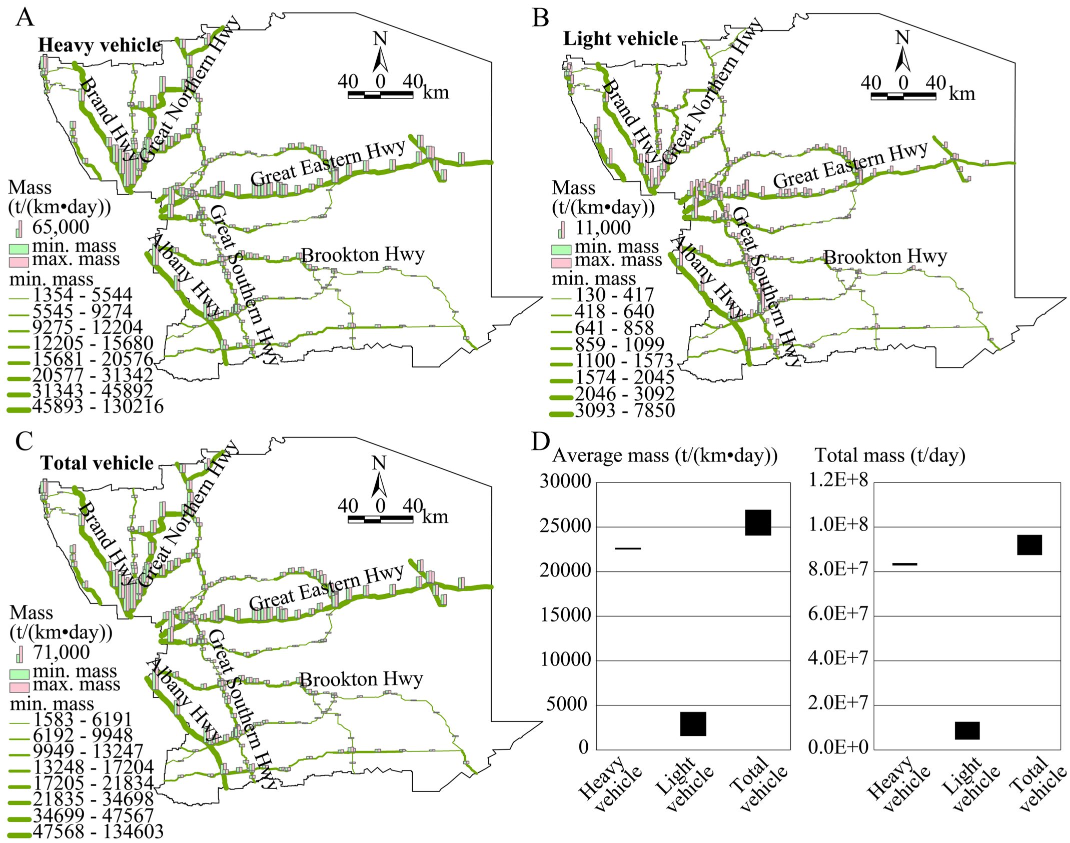

Figure 4-9. Mass distributions for total vehicles (A), light vehicles (B) and total vehicles (C), and their statistical summary (D).

To explain the distinct impacts of heavy and light vehicles on road maintenance, percentages of heavy vehicle volumes and masses among all vehicles are mapped and summarized in Figure 4-10. Results show that the percentage of heavy vehicles on road segments has a diverse range from 6.8% to 56.4% with a mean percentage of 20.9%, but its impact on road maintenance ranges from 51.4% to 96.3%, and the mean impact for all road segments accounts for 82.1% of the road maintenance burden. In contrast, 17.9% of the mean impact on road maintenance burden is related to light vehicles, although its volume is around 79.1%, which is about four times higher than that of heavy vehicle.

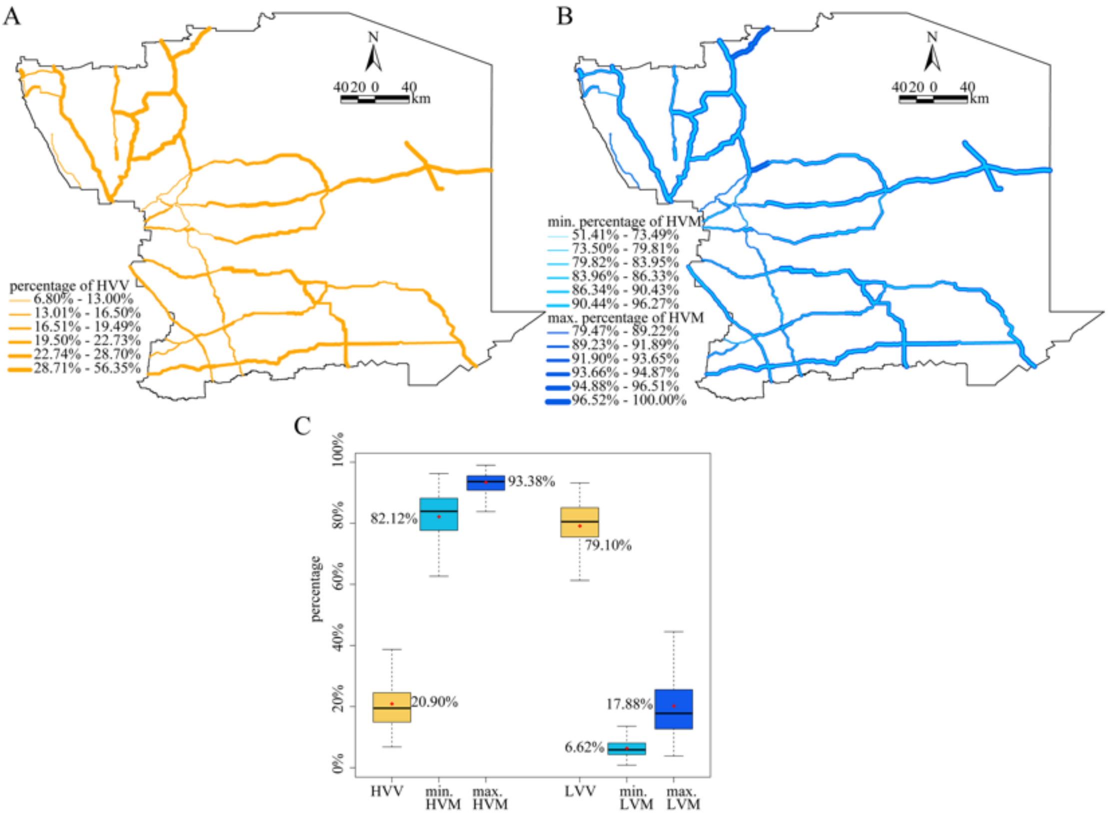

Figure 4-10. Distributions of percentages of heavy vehicle volume (A) and mass (B), and their statistical summary (C).

Practically, grain production areas link densely populated cities with six primary main roads through the Wheatbelt, including Brand Highway, Great Northern Highway, Great Eastern Highway, Brookton Highway, Great Southern Highway and Albany Highway. To further analyse the impacts of heavy vehicles on the road maintenance burden, road segments are grouped by local government area (LGA) groups that are spatially related to the aforementioned six primary main roads. Figure 4-11 shows the distribution of LGA groups, and the distribution of the impact of heavy vehicles related road maintenance burden in these groups. A general trend is that the percentage of heavy vehicle mass increases together with the percentage of heavy vehicle volume, but the relationships vary in different LGAs. The road maintenance burden from heavy vehicles is relatively low at LGAs along Great Southern Highway, and high in LGAs along Great Northern Highway. The impact of heavy vehicles varies at LGAs along Great Eastern Highway with high impact recorded at Dowerin and Toodyay, and low impact at Yilgarn.

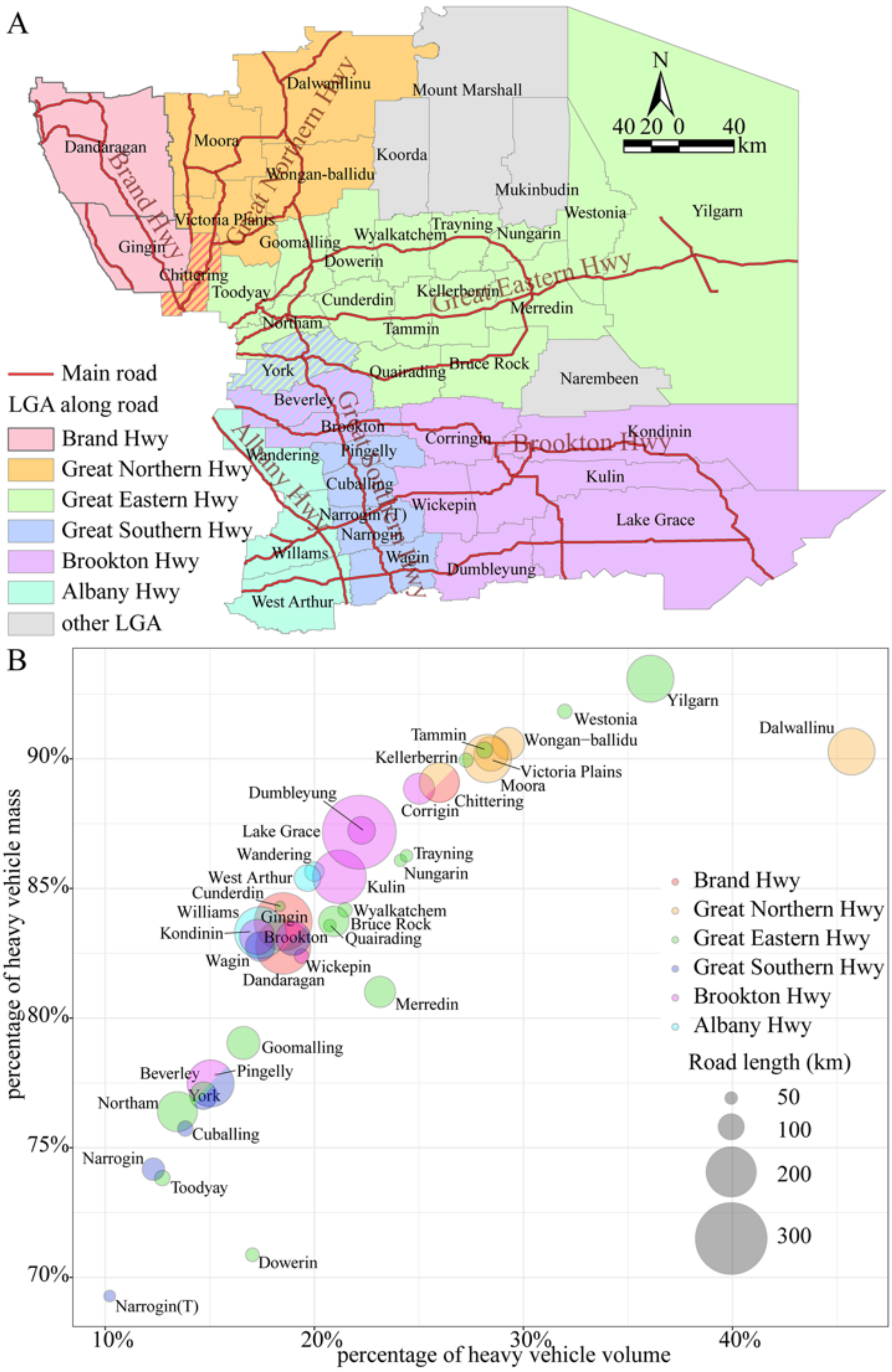

Figure 4-11. Impacts of heavy vehicles on road maintenance burden for local government areas (LGAs).

Even though the prediction accuracy for heavy vehicles is significantly improved by SRK (R^2 = 0.677) as shown in the cross validation, the improvement is still necessary for more accurate prediction. Based on the whole process of data analysis in this study, the prediction accuracy can be improved from three aspects. First, more reasonable explanatory variables of traffic volumes should be explored and added in prediction, such as the percentages of different types of freight transportation served by roads. Both the physical process of pavement deterioration and engineers' experience are required for selecting and determining explanatory variables. Second, reducing errors sourced from data might be helpful for improving prediction accuracy. The data errors usually come from the instrument errors during data collection, measurement errors, and errors from data pre-processing and the combination of multiple sources. Collecting more data at unobserved or sparsely observed locations is also critical for more accurate perdition, since the prediction uncertainty at these locations is usually much higher than the uncertainty at the locations with dense observations. Finally, since this study has proved that segment-based prediction methods can more accurately predict heavy vehicle volumes compared with point-based methods, more segment-based spatial prediction methods need to be proposed and evaluated to improve the prediction accuracy.

4.6 Conclusion

Geostatistical methods have been widely used for spatial prediction and the assessment of traffic issues. Most previous studies use point-based interpolation, but they ignore the critical information of the road segment itself. This can lead to inaccurate predictions, which will negatively affect decision making of road agencies. To address this problem, segment-based regression kriging (SRK) is proposed for traffic volume prediction with differentiation between heavy and light vehicles in the Wheatbelt region of Western Australia (WA). Cross validation reveals that the prediction accuracy for heavy vehicles is significantly improved by SRK (R^2 = 0.677). Specifically, 78% of spatial variance and 53% of estimated uncertainty are improved by SRK for heavy vehicles compared with regression kriging (RK), the best performing point-based geostatistical model. This improvement shows that SRK can provide new insights into the spatial characteristics and spatial homogeneity of a road segment. Implementation results of SRK-based predictions show that the impact of heavy vehicles on road maintenance is much larger than that of light vehicles and it varies across space, and the total impacts of heavy vehicles account for more than 82% of the road maintenance burden even though its volume only accounts for 21% of traffic.

This study reveals that by involving the spatial geometry information of segments, the segment-based spatial interpolation method can more accurately estimate the segment-based spatial data with significant spatial heterogeneity and large spatial geometry compared with point-based interpolations. Due to this characteristic of segment-based methods, they have strong capability in predicting traffic volumes of heavy vehicle freight transportation especially in rural and remote areas, where the roads are longer than urban road segments, the monitoring data are sparsely distributed, and it is difficult to collect global positioning (GPS) data of vehicles with high spatial and temporal resolutions. In addition, segment-based spatial interpolation methods can be used in spatial estimates for geographical objects with geometry of line segments. Besides the above academic contributions of this study, the methods and results also contribute to industrial practice. The application of SRK for predicting the distribution of heavy vehicle volumes indicates that SRK can significantly improve prediction accuracy by considering the spatial geometry of road segments. Segment-based spatial interpolation methods are also a useful approach for the management of heavy and light vehicles, and can inform wise decision making of road maintenance strategies.

Chapter 5 Comprehensive Impacts of Heavy Vehicles and Climate Environment on Road Pavement Performance

5.1 Introduction

This chapter aims to explore the impacts of various factors on pavement infrastructure performance using segment-based spatial stratified heterogeneity analysis. The factors are from multiple sources and include all vehicles and heavy vehicles in particular, climate environment, road characteristics and the local socioeconomic conditions. The segment-based spatial stratified heterogeneity analysis includes two parts: optimal discretisation for segment-based pavement data, and assessing the impact of factors with a segment-based geographical detector. The case study used in this research is the Wheatbelt region in Western Australia (WA), Australia. Based on the case study, the influence mechanism of factors on pavement infrastructure performance is discussed, and future research directions and decision-makings practices are recommended.

5.2 Methodology

Segment-based spatial stratified heterogeneity analysis is performed to explore the relationship between pavement infrastructure performance and its potential spatial variability along road segments. The geographical detector is commonly used for point-based or area-based geographical problems. The method contains four primary models: factor detector, interaction detector, risk detector and ecological detector (Wang et al. 2010, Wang, Zhang, and Fu 2016). In this study, deflections are monitored and analysed for each road segment and the observations are regarded as line segment based data. Therefore, a segment-based geographical detector is utilized by integrating the geometric characteristics of road segments and the geographical detector.

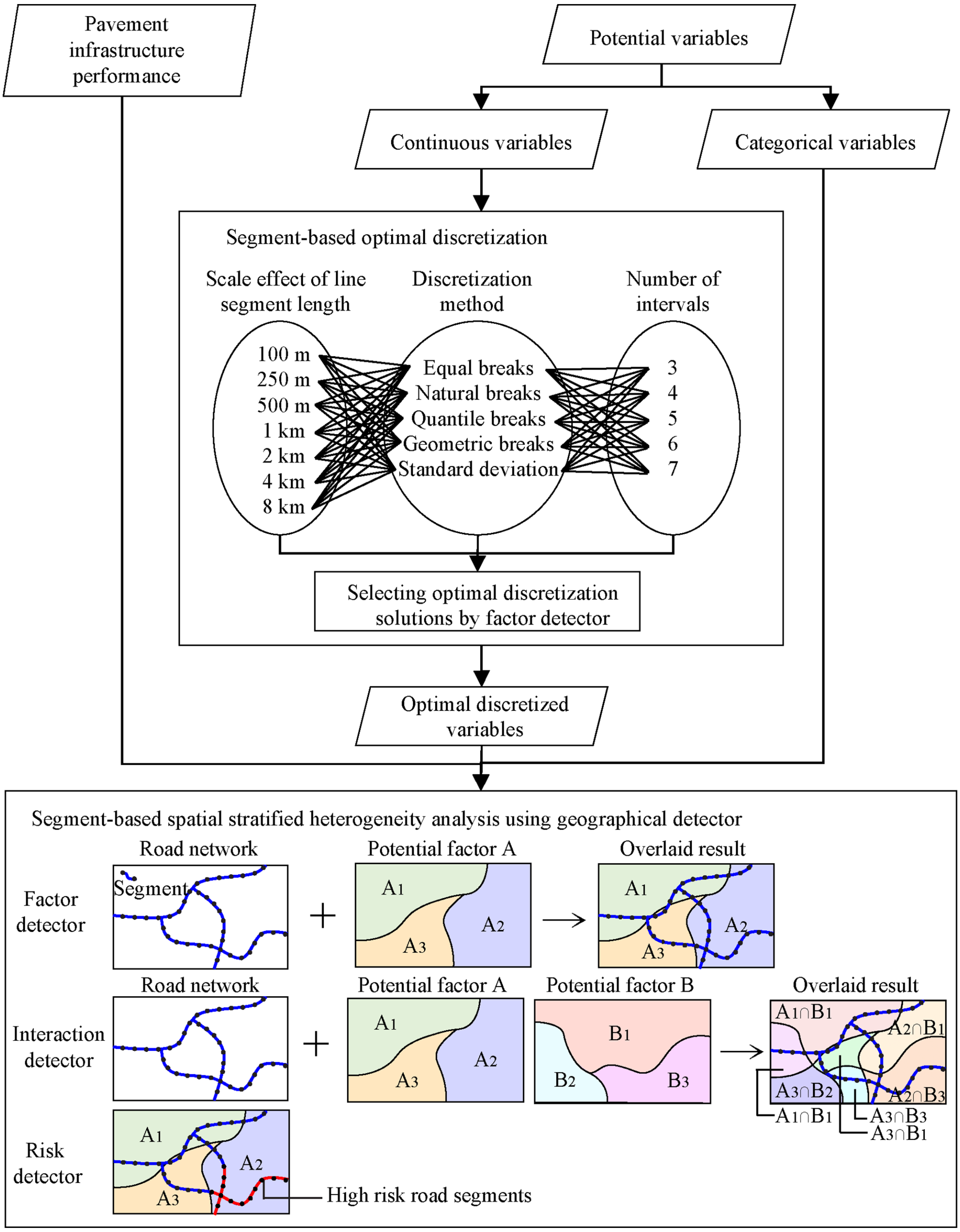

Figure 5-1. Schematic overview of assessing impacts of climate and heavy vehicles on pavement infrastructure performance with segment-based spatial stratified heterogeneity analysis

The methods of segment-based spatial stratified heterogeneity analysis of pavement infrastructure performance are illustrated in Figure 5-1. There are two primary parts in the method: optimal discretisation for the geographical detector and assessing impacts of factors. The two parts are conducted through a three-step process. First, the factor detector model is introduced, since it is the core part of the geographical detector and the calculation of optimal discretisation is based on the factor detector. Next, optimal discretisation is performed to analyse the scale effect to determine the best line segment length for segmenting the road network, and selecting the best combinations of discretisation methods and number of intervals for the optimal discretisation solutions. Finally, spatial stratified heterogeneity is analysed using the factor detector, interaction detector and risk detector models to assess the impacts of variables. In terms of the data and calculation processes in this study, we develop a "GD" R package for optimal discretisation and spatial stratified heterogeneity analysis using the geographical detector, which can be freely downloaded from the Comprehensive R Archive Network (CRAN) (https://cran.r-project.org/web/packages/GD/index.html). A sample dataset sourced from this thesis is also provided so that users can easily access the models and perform their own experiments.

5.2.1 Segment-based factor detector model

A key part of the geographical detector is the factor detector model, which presents the relative importance of the determinants of geographical problems (Wang et al. 2010, Wang, Zhang, and Fu 2016). In this study, the factor detector model is used twice. First, it is used for optimal discretisation with the segment-based geographical detector. Once the optimal discretisation solutions are determined, the factor detector model is then applied to the segment-based spatial stratified heterogeneity analysis for exploring the relative importance of the potential variables of pavement infrastructure performance. The mechanism of the segment-based factor detector is shown in Figure 5-1. The segment-based factor detector is measured by a Q value, which presents the consistency of spatial patterns between pavement infrastructure performance and its potential variables. The Q value is equal to one minus the ratio of accumulated dispersion variance of deflections within sub-regions to that of the whole road network:

$$Q = 1 - (\textstyle\sum_{u=1}^{s} N_{A,u}\sigma_{A,u}^{2})/N\sigma^{2} \quad (5\text{-}1)$$

where A is a segment-level variable that its observations are distributed along the road line segments with the same segmenting length, $N_{A,u}$ is the number of observations of pavement infrastructure performance on the road segments distributed on the uth ($u = 1, \dots, s$) sub-regions that are determined by segment-level variable A, the dispersion variance of these observations is $\sigma_{A,u}^2$, and N and σ^2 are the number and dispersion variance of all observations of pavement infrastructure performance on the whole road network. The Q value reflects the relative importance of variables, ranging from 0 to 1. A variable with a large Q value has relatively higher importance than a variable with a small Q value. The result of $Q = 1$ due to $\sigma_{A,u}^2 = 0$ and $\sigma^2 \neq 0$ means that the spatial pattern of pavement infrastructure performance is identical to the distribution of variable A, and the result of $Q = 0$ shows that variable A is completely unrelated to pavement infrastructure performance seen from the perspective of segment-based spatial stratified heterogeneity.

5.2.2 Optimal discretisation for segment-level variables

Since the input of the geographical detector should be categorical variables, an optimal discretisation framework is utilized to select the optimal discretisation solutions for discretising continuous variables along road segments (Figure 5-1). The optimal discretisation framework includes three objectives: assessing the impacts of scale effect of line segments to determine the best length for segmenting the road network, selecting the best combination of discretisation method and number of intervals for each variable that enables the largest Q value in the segment-based factor detector model, and calculating optimal discretised segment-based continuous variables.

Scale effect is a common phenomenon in geospatial problems due to the modifiable spatial unit defined manually according to the understanding and experience of researchers (Jelinski and Wu 1996, Ju et al. 2016). Spatial effect means that changes in the size of a spatial unit usually lead to different spatial analysis results (Jelinski and Wu 1996), so scale effect analysis is critical for selecting an optimal spatial unit for reasonable geospatial analysis. For the general geographical detector for point or area based data, scale effect analysis aims at selecting the best grid size using the relative importance (Q value) of variables, where stable ranks of Q values indicate the optimal spatial unit (Ju et al. 2016). In this study, the best length of line segment for segmenting the road network will be obtained through the comparison of associations between line segment lengths and the variations of relative importance Q values. The optimal length of a line segment is selected when the ranks of Q values are stable. According to the geometric characteristics of the segments distributed on the road network, seven lengths of line segments in the segment-based geographical detector are utilized for the scale effect analysis, including 100 m, 250 m, 500 m, 1 km, 2 km, 4 km and 8 km, and the corresponding number of segments on the road network are 18 660, 7 523, 3 812, 1 958, 1 031, 567 and 335.

In addition to selecting the optimal length of line segments, the best combinations of discretisation methods and numbers of intervals will be determined for discretising continuous variables. Under the optimal length of line segments, different discretisation methods and numbers of intervals can generate various break values. In this study, five commonly used unsupervised discretisation methods are utilized for discretising continuous variables, including equal breaks, natural breaks, quantile breaks, geometric breaks and standard deviation (SD) breaks. The five methods have their respective advantages in dividing the range of data values into specified intervals by considering data range, data distribution, data within or between intervals, and statistical characteristics (Fischer and Wang 2011, Cao, Ge, and Wang 2013). All continuous variables are divided into ranges of 3 – 7 intervals using the five discretisation methods. The ranges of 3 – 7 intervals are proper numbers of intervals for most of the geographical variables, since if the number of intervals is too small, spatial stratified heterogeneity cannot be reflected by the variables, and if they are too large, data will be scattered across space. The relative importance (Q values) are computed using a factor detector model for all combinations of discretisation methods and numbers of intervals, and the largest Q values determine the best parameter combinations for discretising continuous variables.

Finally, once the optimal length of line segments is selected, and the best combinations of discretisation methods and numbers of intervals are determined for segment-based continuous variables, the road network will be segmented and the continuous variables are discretised and converted to corresponding categorical variables. Thus, the discretised variables and categorical variables, such as soil type and surface type, are equally regarded as the potential variables of pavement infrastructure performance and input for the segment-based geographical detector.

5.2.3 Segment-based interaction detector and risk detector models

In the segment-based geographical detector, the interaction detector is utilized to explore the interactive impacts of segment-based variables on the pavement infrastructure performance, and a risk factor is computed to explore the road segments with high or low risk of damage. The interaction detector compares the importance of two combined potential variables to their independent importance to evaluate if the variables are enhanced or weakened by each other, or their impacts are independent. Figure 5-1 shows the interaction of two potential variables A and B, and their relationship with the distribution of pavement infrastructure performance. The importance comparison of the interaction variables and the independent variables are computed by the interaction detector as follows (Wang et al. 2010):

$$\begin{cases} Q_{A\cap B} < \min(Q_A, Q_B) & \text{Nonlinear} - \text{weaken} \\ \min(Q_A, Q_B) \le Q_{A\cap B} \le \max(Q_A, Q_B) & \text{Weaken/Uni} - \text{enhance} \\ \max(Q_A, Q_B) < Q_{A\cap B} < (Q_A + Q_B) & \text{Bi} - \text{enhance} \\ Q_{A\cap B} = (Q_A + Q_B) & \text{Independent} \\ Q_{A\cap B} > (Q_A + Q_B) & \text{Nonlinear} - \text{enhance} \end{cases} \tag{5-2}$$

where $Q_{A\cap B}$ is the relative importance of the interaction variables, and Q_A and Q_B are the respective relative importance of variables A and B. In equation (5-2), the relative importance is gradually increased from "nonlinear-weaken" to "nonlinear-enhance".

Further, the risk detector computed with a *t*-test is utilized to explore the spatial distributions of relative risks, which are computed by the difference of average values within sub-regions defined by intervals of a potential variable (Wang et al. 2010). In this study, the average pavement deflections within sub-regions are calculated to reflect the relative conditions of road damage that are linked with the spatial patterns of potential variables. The average pavement deflection D_u within uth sub-region in risk detector analysis is calculated by:

$$D_u = \sum_{j=1}^{M_{u,j}} D_{u,j} / (LM_{u,j}) \tag{5-3}$$

where $D_{u,j}$ is the pavement deflection on jth road segment within uth sub-region, $M_{u,j}$ is the total number of road segments within the sub-region, and L is the optimal length of line segments determined by scale effect analysis. The average pavement deflection D_u reflects the relative risk of road damage within an interval of a variable. A large value of D_u indicates a relatively high risk within a certain sub-region defined by an interval of a variable. Figure 5-1 illustrates the spatial distribution of road segments with the highest relative risks of pavement deflections.

5.3 Study area and data

5.3.1 Road condition data

The Wheatbelt region is located in southwestern WA and is made up of 42 local government authorities (LGAs) with an area of 154 862 km^2. It is the primary grain production region in WA and includes important mining activities that generate substantial heavy haulage vehicle traffic (Figure 5-2). There are 280 road segments distributed on six major roads, including Brand Highway, Great Northern Highway, Great Eastern Highway, Brookton Highway, Great Southern Highway and Albany Highway. These road segments link the state capital (Perth) and major regional ports within the Wheatbelt region. Road maintenance, such as resurfacing, is a vital and regular construction task for road management authorities ***(Chong et al. 2016)***.

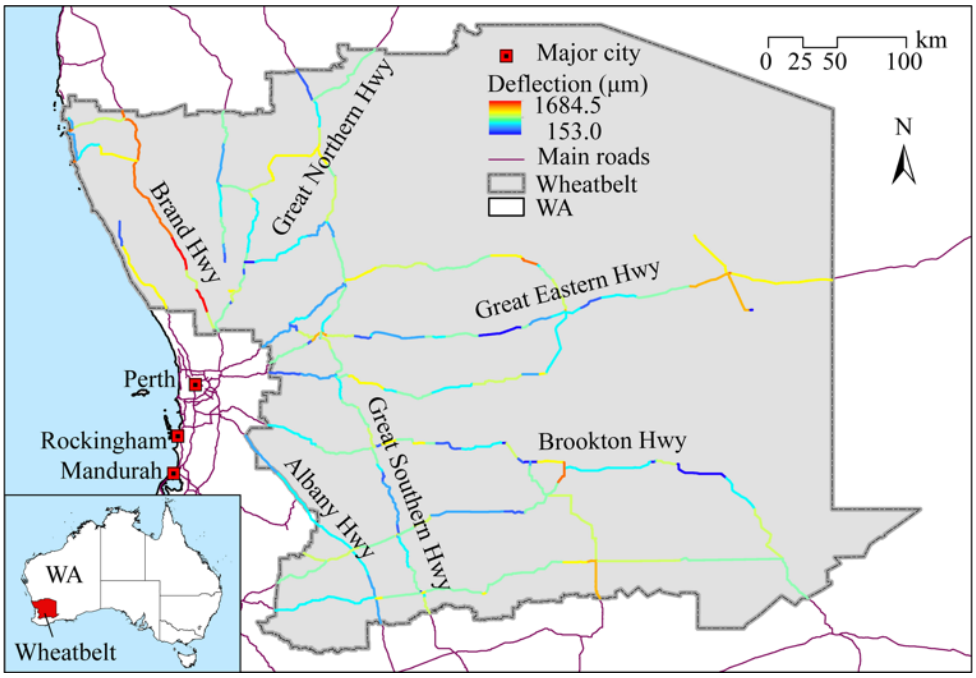

Figure 5-2. Spatial distribution of pavement deflections across road network in the study area

Road conditions are assessed via deflection measurements using a Dynatest 8000 series Falling Weight Deflectometer (FWD) and calibrated with Calibration Method WA 2060.5 by Main Roads, WA (Main Roads Western Australia 2017b, a). Deflection is a pavement strength indicator measured as the maximum depression in the surface of pavement under a standard load. Figure 1 shows the spatial distributions of mean deflections on road segments. Deflections on the 280 road segments vary across the road network, ranging from 153.0 μm to 1684.5 μm with the average value of 383.6 μm.

5.3.2 Potential variables

The potential variables of pavement infrastructure performance are collected from multiple data sources. They are pre-processed to have the same spatial and temporal scales with pavement infrastructure performance data, where the identical spatial scale is the road network in the Wheatbelt region, WA, and temporal scale is the year 2015. The potential variables and their respective data sources are listed in Table 5-1. Based on the collected data, 24 potential variables are derived and they are divided into four categories. Two primary categories of variables are vehicles and heavy vehicles (C1), and climate and environment factors (C2), and another two categories of auxiliary variables are road characteristics (C3), and socioeconomic factors (C4). Variables in different categories have comprehensive impacts on the pavement conditions. Figure 5-3 displays the spatial distributions of all 24 variables in the order listed in Table 5-1.

Table 5-1. Descriptions of potential variables of pavement infrastructure performance

Category	No.	Code	Name (Unit)	Data source
Vehicles and heavy vehicles (C1)	1	vlmsum	Total volume of vehicles	Main Roads Western Australia (Main Roads Western Australia 2015) and calculating using segment-based regression kriging methods (Song, Wang, et al. 2018).
	2	pcthvvlm	Percentage of heavy vehicle volume (%)	
	3	masssum	Total mass of vehicles (t/(km·day)	
	4	pcthvmass	Percentage of heavy vehicle mass (%)	
Climate and environment (C2)	5	ap	Annual precipitation (mm)	Bureau of Meteorology, Australia (Bureau of Meteorology Australian Government 2017, Jones, Wang, and Fawcett 2009).
	6	maxtemp	Annual maximum temperature (°C)	Land surface temperature (LST) MOD11A2 from Moderate Resolution Imaging Spectroradiometer (MODIS) (Wan, Hook, and Hulley 2015).
	7	mintemp	Annual minimum temperature (°C)	
	8	meantemp	Annual mean temperature (°C)	
	9	tempdif	Annual temperature difference (°C)	
	10	soiltype*	Soil type	2016 State of the Environment (SoE) Land Australian Soil Classification Orders dataset (Ashton and McKenzie

				2001, State of the Environment in Australia 2017).
	11	rzsm	Root-zone soil moisture (%)	Bureau of Meteorology, Australia, and the Australian Soil Resources Information System (ASRIS) dataset (Johnston et al. 2003, Bureau of Meteorology Australian Government 2017).
	12	usm	Upper soil moisture (%)	
	13	lsm	Lower soil moisture (%)	
	14	dsm	Deep soil moisture (%)	
	15	dd	Deep drainage (mm)	
	16	ae	Actual evapotranspiration (mm)	
	17	evi	Enhanced vegetation index (EVI)	Enhanced vegetation index (EVI) MOD13A2 from Moderate Resolution Imaging Spectroradiometer (MODIS) (EARTHDATA 2017).
Road characteristics (C3)	18	ravnw*	Restricted access vehicles (RAV) network	Main Roads Western Australia.
	19	speed*	Road speed limit (km/h)	
	20	surftype*	Road surfacing type	
Socioeconomic factors (C4)	21	popbf1	Population within 1 km	Population data with 1-km spatial resolution is from Gridded Population of the World fourth version (GPWv4) (NASA 2016b).
	22	popbf5	Population within 5 km	
	23	popbf10	Population within 10 km	
	24	wpop	Weighted population within 50 km	

* The marked variables are categorical variables, and other variables are continuous variables.

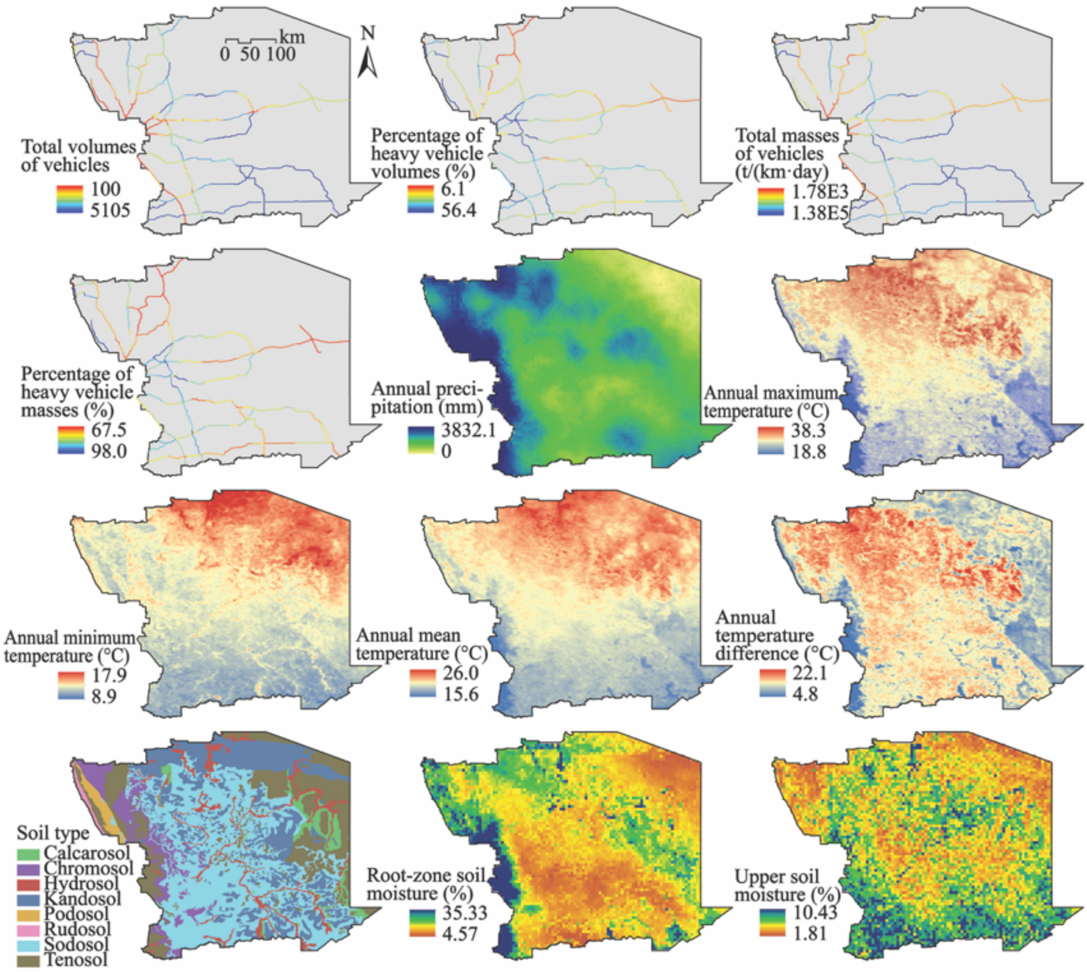

Figure 5-3. Spatial distribution of potential variables of pavement infrastructure performance (part 1)

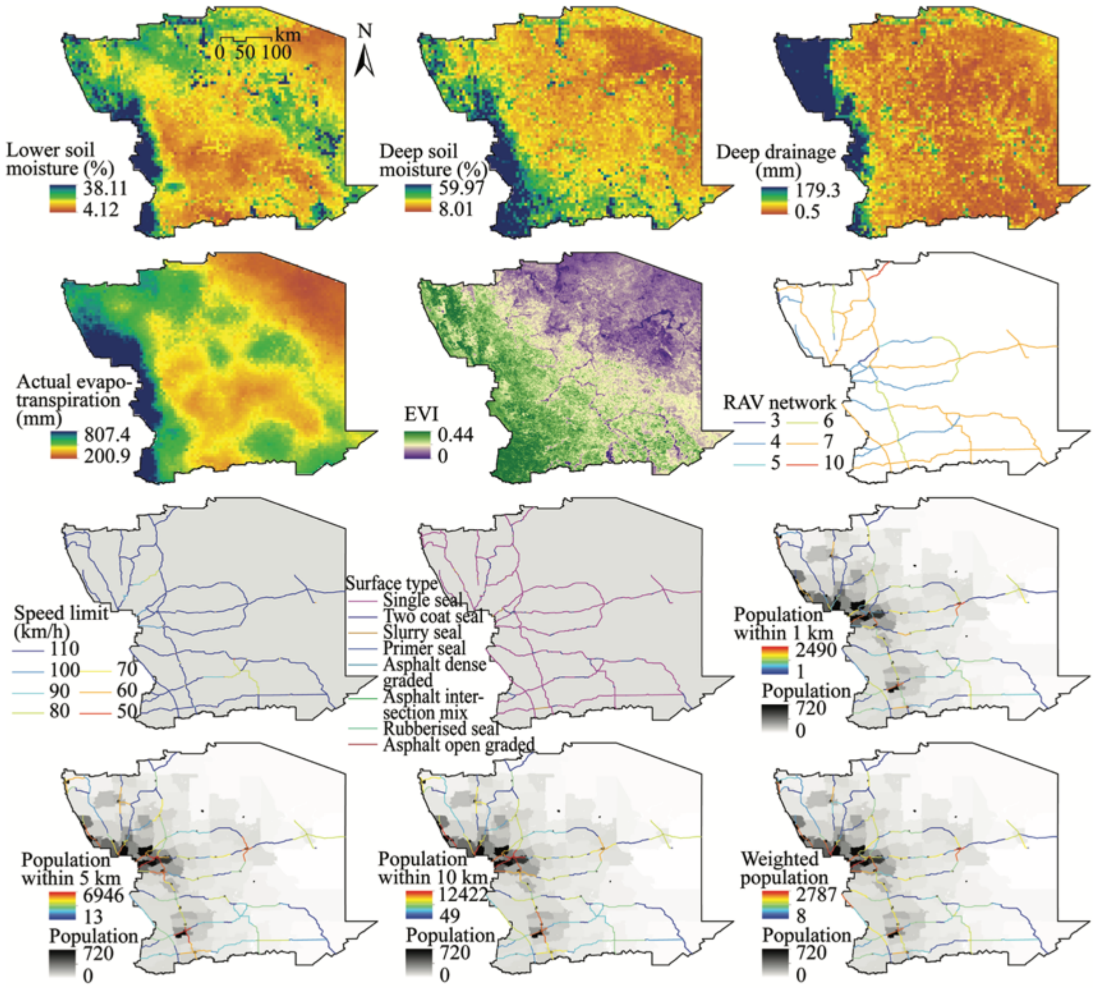

Figure 5-3. Spatial distribution of potential variables of pavement infrastructure performance (part 2)

The four categories of potential variables are carefully pre-processed from the raw data to accurately reflect the impacts of the variables. The first category is the variables of vehicles and heavy vehicles. Traffic volumes are directly linked with pavement infrastructure performance, where heavy vehicles are a primary contributor due to the heavy mass. In general, the weight of a standard light vehicle is merely 1.65 t and the gross vehicle mass (GVM) is limited to 4.5 t in Australia (Department of Transport - The Government of Western Australia 2016), but the mass of heavy vehicles used for freight transportation ranges from 42.5 t to 147.5 t (Main Roads Western Australia 2016a). Thus, the total traffic volumes and masses, and the respective percentages of heavy vehicles are calculated using segment-based regression kriging (SRK) methods (Song, Wang, et al. 2018) with traffic statistical data provided by Main Roads, WA (Main Roads Western Australia 2015). SRK is a spatial prediction model for line segment-based spatial data, such as road properties and traffic conditions, by involving the spatial characteristics and spatial homogeneity of line segments (Song, Wang, et al. 2018). Compared with raw data released by Main Roads, WA, and the data predicted using traditional aspatial and point-based spatial methods, SRK provides more accurate prediction results with significantly reduced errors and autocorrelations of residuals.

Another critical category of variables is related to the on-road and near-road climate and environmental conditions, including precipitation, temperature, soil type, soil moisture and vegetation in the Wheatbelt region, WA, in 2015. The annual precipitation data with a spatial resolution of 5 km is sourced from the Bureau of Meteorology in Australia (Bureau of Meteorology Australian Government 2017). This precipitation dataset is calculated based on daily precipitation grids produced from approximately 6,500 rain gauge stations across Australia (Jones, Wang, and Fawcett 2009). Temperature variables including maximum temperature, minimum temperature, mean temperature and the calculated temperature difference during 2015 are derived from 1-km spatial resolution 8-Day L3 Global Land Surface Temperature (LST) and Emissivity product (MOD11A2) from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Wan, Hook, and Hulley 2015). Spatial data of soil type distributions is sourced from the 2016 State of the Environment (SoE) Land Australian Soil Classification Orders dataset (Ashton and McKenzie 2001, State of the Environment in Australia 2017). Soil moisture variables with a spatial resolution of 5 km are sourced from the Bureau of Meteorology, Australia, and the Australian Soil Resources Information System (ASRIS) dataset (Johnston et al. 2003, Bureau of Meteorology Australian Government 2017). Soil type includes Calcarosol, Chromosol, Hydrosol, Kandosol, Podosol, Rudosol, Sodosol and Tenosol in the Wheatbelt region. Soil moisture reflects the relative soil water storage capacity within a soil layer between a certain range of depths. Variables of soil moisture data include root-zone soil moisture, upper soil moisture, lower soil moisture, deep soil moisture, deep drainage, and actual evapotranspiration (Bureau of Meteorology Australian Government 2017). Root-zone soil moisture is the sum of available water in the upper and lower soil layers in the top 10 cm and 10 cm - 1 m, respectively. Deep soil moisture represents the percentage of available water within the 1 - 6 m soil layer, which is determined based on the assumption that deep-rooted vegetation can access water down to 6 m (Bureau of Meteorology Australian Government 2017). Deep drainage is the water draining from the bottom of the deep soil layer to the groundwater and represents diffuse groundwater recharge (Keese, Scanlon, and Reedy 2005). Actual evapotranspiration is the estimated total evapotranspiration from vegetation, soil and groundwater using event-based methods and adaptive analytical models (Gash 1979, Van Dijk and Bruijnzeel 2001). Ground vegetation conditions are explained by 1-km spatial resolution enhanced vegetation index (EVI) data, which is collected from the Terra Vegetation Indices 16-Day L3 MOD13A2 product from MODIS (EARTHDATA 2017).

In addition to the variables of vehicles and climate, road characteristics and socioeconomic factors are also included as potential variables of pavement infrastructure performance. In WA, the restricted access vehicles (RAV) network used by Main Roads, WA, is a critical guideline for heavy vehicle services and road management operations for staff, operators and consultants in Main Roads and LGAs (Main Roads Western Australia 2017c). The RAV network defines ten categories of heavy vehicles and corresponding roads they can access (Main Roads Western Australia 2017e). Spatial vector data of the RAV network is provided by Main Roads WA (Main Roads Western Australia 2016b). In addition, Main Roads WA also provides speed limit spatial vector data (Main Roads Western Australia 2017d) and road surface type data, where surface type includes single seal, two coat seal, slurry seal, primer seal, asphalt dense graded, asphalt intersection mix, rubberised seal and asphalt open graded in the Wheatbelt region. For socioeconomic factors, populations near road segments are calculated to reflect the potential utilization of roads by surrounding residents. Population data with 1-km spatial resolution is obtained from Gridded Population of the World fourth version (GPWv4) (NASA 2016b), and the calculated variables include population within 1-km, 5-km and 10-km buffer areas of road segments, and the inverse weighted population within 50-km buffer areas (Song, Tan, et al. 2018).

5.4 Experiments and Results

5.4.1 Optimal discretisation

During the optimal discretisation process, seven lengths of line segments are analysed in the scale effect analysis, and five unsupervised discretisation methods and five intervals are included in selecting the best parameters for segmenting the road network and discretising continuous variables. In total, 175 groups ($7 \times 5 \times 5$) of experiments are performed for each of the 20 continuous variables listed in Table 1 for optimal discretisation analysis. In the experiments, the best combinations of discretisation methods and numbers of intervals are firstly selected by the comparison of relative importance using Q values for each of the seven lengths of line segments. Figure 5-4 shows the comparison of Q values and their ranks with the line segment lengths, where the best combinations of discretisation methods and numbers of intervals are set for the variables. Ranks of Q values show that when line segment length is less than 500 m, the ranks of variables (especially the top half ranks) are relatively stable. When line segment length is larger than 500 m, the ranks of variables are changed and the number of variables with significant relationships with pavement infrastructure performance are reduced. Thus, in the scale effect analysis, 500-m line segments are used for segmenting the road network and generating segment-based explanatory and response variables. The result of 500-m line segments is also consistent with the regional practice on sealing design by Main Roads, WA. Meanwhile, Figure 5-5 shows the process for selecting the best combinations of discretisation methods and the number of intervals for discretising continuous variables under the line segment length of 500 m. For each continuous variable, the best combination with the largest Q value is selected from 25 combinations formed by five discretisation methods and five intervals. The best combination is also calculated for the scenarios of other line segment lengths, and the results are utilized in the analysis of ranks of Q values (Figure 5-4). The results of discretising continuous variables are shown in Figure 5-6, and the best discretisation methods and numbers of intervals for continuous variables are summarized in Table 5-2, together with the categorical variables to be used in the segment-based geographical detector analysis. Results show that the combination of discretisation methods and the number of intervals have no relationship with Q values. The best combinations might be associated with the distributions of variable data and the relationships between spatial patterns of pavement infrastructure performance and the potential variables.

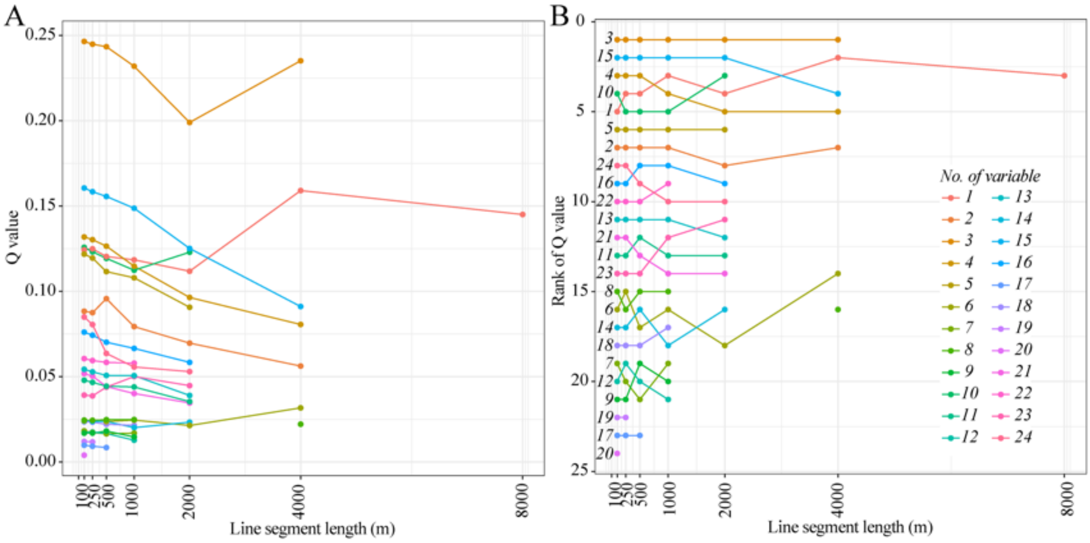

Figure 5-4. Scale effects of line segment length on Q values (A) and ranks of variables (B)

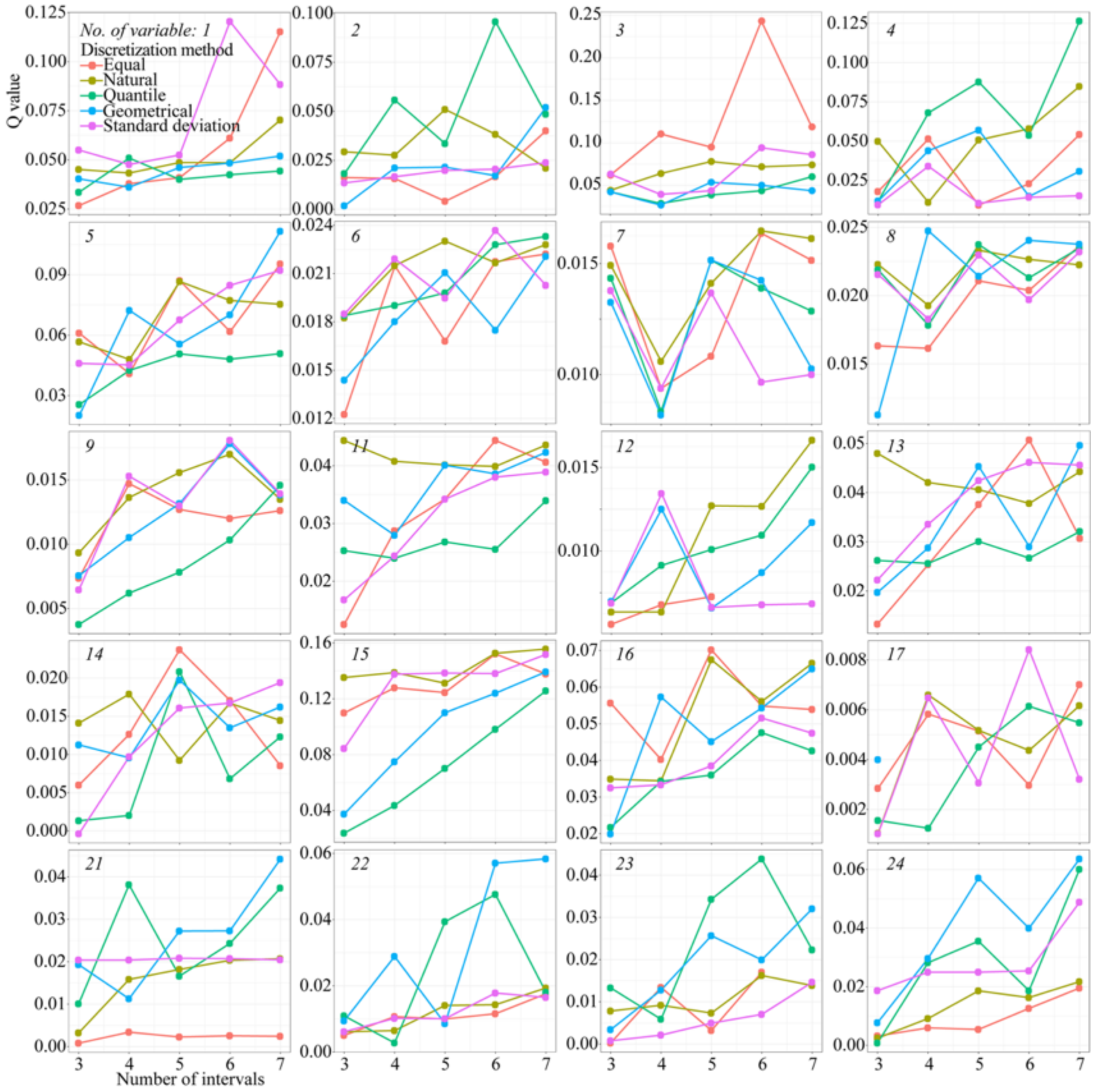

Figure 5-5. Process of selecting the best combinations of discretisation methods and number of interactions for continuous variables

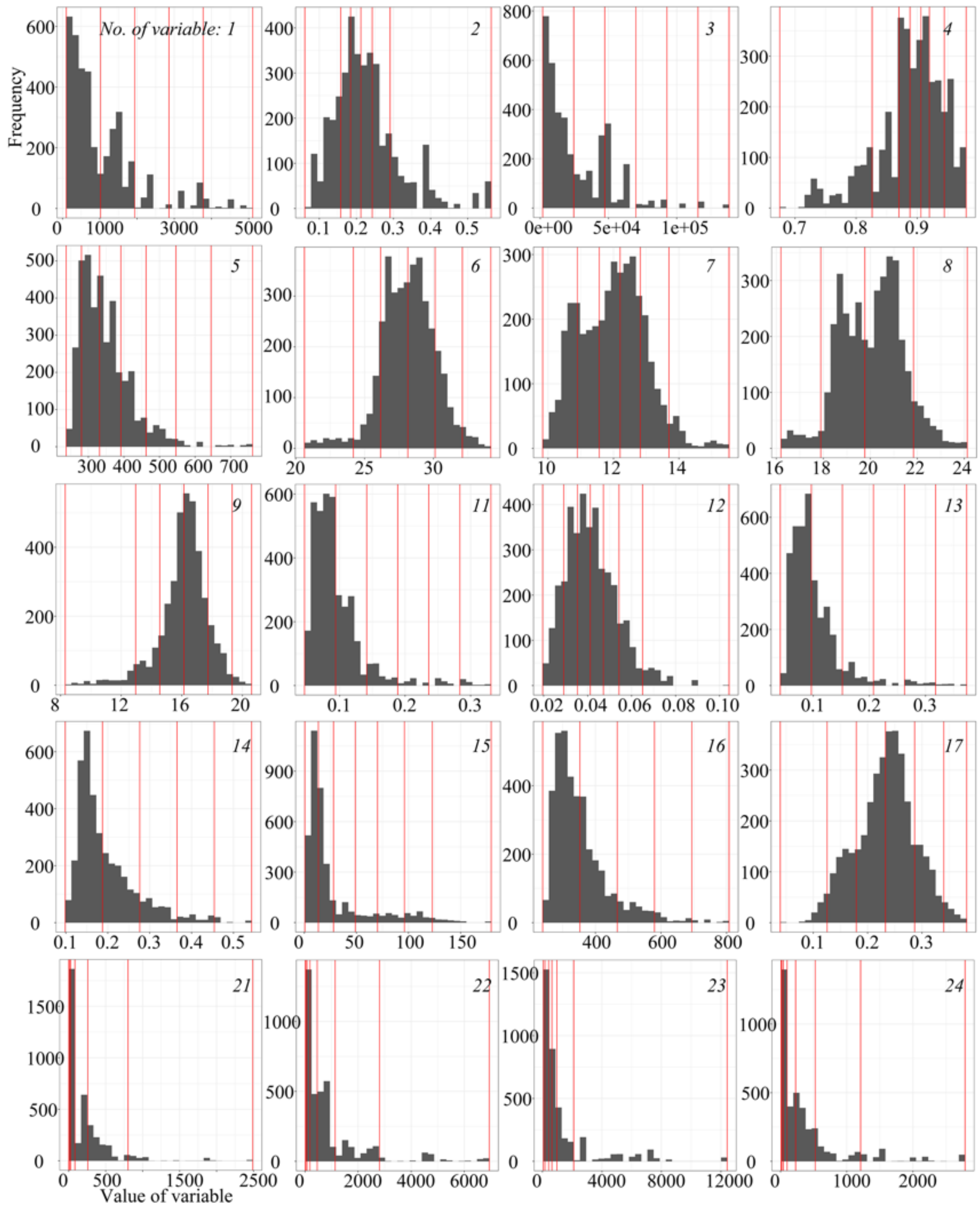

Figure 5-6. Results of optimal discretisation of continuous variables

Table 5-2. Summary of best discretisation methods and numbers of intervals for continuous variables

No.	Code	Min	Max	Method	Number of intervals
1	vlmsum	100	5105	SD	7
2	pcthvvlm	6.1	56.4	quantile	6

3	masssum	1780.1	138391.3	equal	6
4	pcthvmass	67.5	98.0	quantile	7
5	ap	237.6	761.8	geometric	7
6	maxtemp	20.7	33.9	SD	6
7	mintemp	9.8	15.4	natural	6
8	meantemp	16.4	24.0	geometric	4
9	tempdif	8.6	20.6	SD	6
10	soiltype	Categorical variable, including Calcarosol, Chromosol, Hydrosol, Kandosol, Podosol, Rudosol, Sodosol and Tenosol.			8
11	rzsm	4.64	33.11	equal	6
12	usm	1.96	10.43	natural	7
13	lsm	4.12	37.33	equal	6
14	dsm	9.84	54.31	equal	5
15	dd	0.5	179.3	natural	7
16	ae	239.3	807.4	equal	5
17	evi	0.04	0.38	SD	6
18	ravnw	Categorical variable, including 3, 4, 5, 6, 7 and 10.			6
19	speed	Categorical variable, including 50, 60, 70, 80, 90, 100 and 110 (km/h).			7
20	surftype	Categorical variable, including single seal, two coat seal, slurry seal, primer seal, asphalt dense graded, asphalt intersection mix, rubberised seal and asphalt open graded.			8
21	popbf1	1	2490	geometric	7
22	popbf5	13	6946	geometric	7
23	popbf10	49	12422	quantile	6
24	wpop	8	2787	geometric	7

5.4.2 Segment-based factor detector

Under the 500-m line segment scenario for segmenting the whole road network in the Wheatbelt region, the segment-based factor detector is performed for all potential variables, including category and discretised segment-level variables. Figure 5-7 shows the Q values and their ranks of variables with significant relationships with pavement deflections. The variables which have no significant Q values are removed. The removed variables include EVI, traffic speed limit and road surface type. In general, variables from the categories of vehicles and heavy vehicles, and climate and environment, make more contributions to the pavement deflections than the variables of road characteristics and socioeconomic factors. All four variables of vehicles and heavy vehicles are among the top-quartile ranks of Q values. The relative importance of total masses of vehicles ($Q = 0.243$) and deep drainage ($Q = 0.156$) are much higher than other variables. Weighted population within 50 km ($Q = 0.064$) and RAV network ($Q = 0.022$) are the variables that have the largest contributions among their respective category of socioeconomic factors and road characteristics.

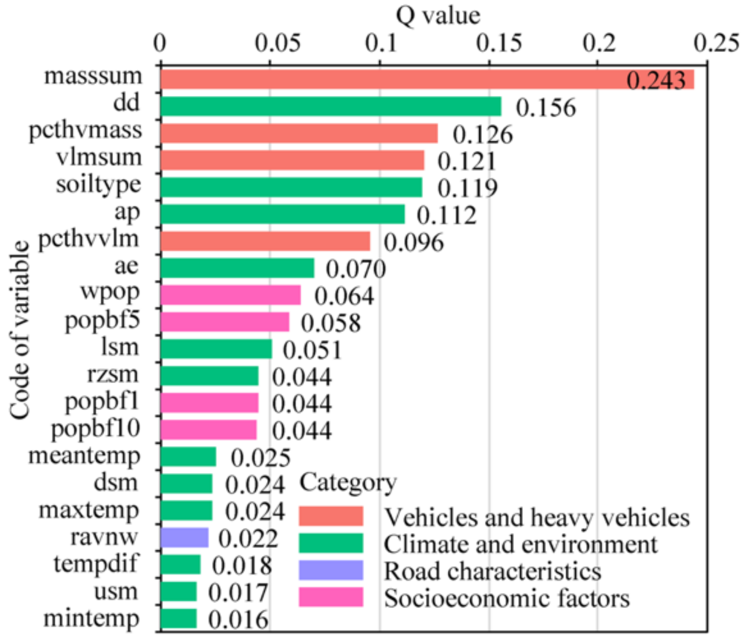

Figure 5-7. Relative importance of potential variables explored by factor detector

5.4.3 Segment-based interaction detector

In this study, 276 pairs of interactions among 10 types of category interactions are computed between the 24 potential variables in the 4 categories. Figure 5-8 shows the impacts of all interactions between potential variables, including variable interactions, category interactions, Q values and ranks, where the top 20 interactions are marked by the ranks. Table 5-3 lists the top 20 interactions, which are all nonlinearly enhanced by both variables. The top 20 interactions are identified in the category interactions of (1) vehicles and heavy vehicles (C1 ∩ C1), (2) vehicles and heavy vehicles, and climate and environment (C1 ∩ C2), (3) vehicles and heavy vehicles, and socioeconomic factors (C1 ∩ C4), and (4) climate and environment, and socioeconomic factors (C2 ∩ C4). Half of the top 20 interactions are the category interaction of vehicles and heavy vehicles, and climate and environment (C1 ∩ C2), four interactions are included in the category interactions of vehicles and heavy vehicles (C1 ∩ C1), and another four interactions are between the categories of climate and environment, and socioeconomic factors (C2 ∩ C4).

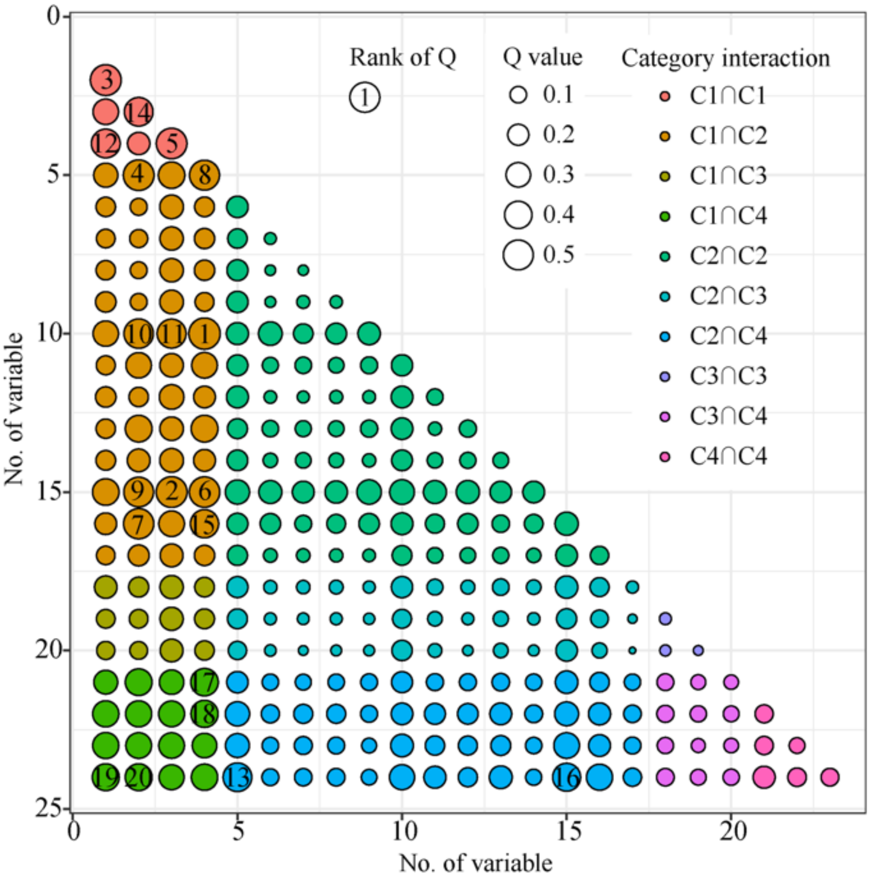

Figure 5-8. Relative importance of interactions of variables and categories derived by interaction detector

Table 5-3. Interactions between variables of pavement deflections (top 20 interactions)

Category	Variable	C1: Vehicles and heavy vehicles				C2: Climate and environment	
		vlmsum	pcthvvlm	masssum	pcthvmass	ap	dd
C1: Vehicles and heavy vehicles	vlmsum						
	pcthvvlm	0.543*					
	masssum		0.451				
	pcthvmass	0.457		0.532			
C2: Climate and environment	ap		0.535		0.505		
	soiltype		0.481	0.464	0.566*		
	dd		0.496	0.544	0.525		
	ae		0.516		0.435		
C4: Socio-economic factors	popbf1				0.407*		
	popbf5				0.393		
	wpop	0.385	0.384			0.453*	0.423

* The largest interaction within each category, including C1∩C1, C1∩C2, C1∩C4, and C2∩C4.

The interaction that contributes the most to the pavement deflections is the percentage of heavy vehicle mass and soil type ($Q = 0.566$), and the interaction with the second largest relative importance is the interaction between total mass of vehicles and soil deep drainage ($Q = 0.544$). Both belong to the category interaction between vehicles and heavy vehicles, and climate and environmental factors (C1 ∩ C2). The results indicate that the pavement infrastructure performance is significantly related to the interactive impacts between vehicles and heavy vehicles, and the climate and environmental conditions, and the impacts are nonlinearly enhanced by both categories of variables. Heavy vehicles are an important contributor among vehicles, and it has strong interactions with climate and environmental conditions. In addition to the soil type and soil deep drainage, precipitation and actual evapotranspiration also have strong interactions with the variables of vehicles and heavy vehicles, especially the percentages of heavy vehicle volume and mass.

The interactions that have third and fourth highest relative importance are related to the category interaction within vehicles and heavy vehicles (C1 ∩ C1), including the interaction between total volume of vehicles and the percentage of heavy vehicles ($Q = 0.543$), and the interaction between total mass of vehicles and the percentage of heavy vehicle mass ($Q = 0.532$). Results of the interaction of vehicles and heavy vehicles reveal that the volumes of vehicles and heavy mass have significant influence on the pavement infrastructure performance, and their impacts are nonlinearly enhanced.

In addition, socioeconomic factors also have strong interactive impacts with variables from the categories of vehicles and heavy vehicles, and climate and environment. The interaction between population within 1 km from road segments and percentage of heavy vehicle mass ($Q = 0.407$) is the most important interaction among the category interaction between socioeconomic factors and vehicles and heavy vehicles. Meanwhile, the interaction between weighted population within 50 km of road segments and annual precipitation ($Q = 0.453$) has the largest contribution in the category interaction between socioeconomic factors and the climate and environmental conditions.

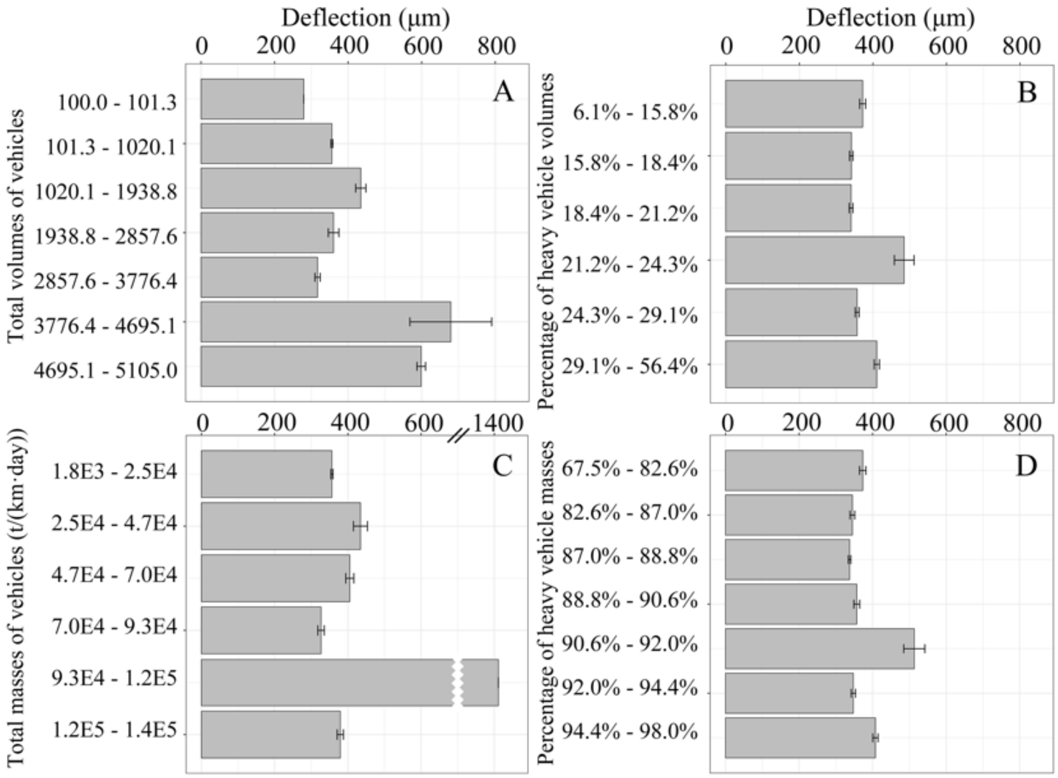

Figure 5-9. Levels of risk within sub-regions of variables within the category of all vehicles and heavy vehicles

5.4.4 Segment-based risk detector

The segment-based risk detector reveals the road segments with pavement deflections at high or low risks in different sub-regions of variables. The risks of pavement deflections are calculated using the segment-based risk detector for variables in the four categories, including vehicles and heavy vehicles (C1, Figure 5-9), climate and environment (C2, Figure 5-10), road characteristics (C3, Figure 5-11), and socioeconomic factors (C4, Figure 5-12), where the variables that have no significant relationships with pavement deflections are removed. To deeply understand the spatial patterns of pavement deflections at high or low risks, five levels of risks are defined for the sub-regions of variables, including very high risk, high risk, medium risk, low risk and very low risk. The definitions and descriptions of pavement infrastructure performance risk levels are listed in Table 5-4. According to the definition, risks of pavement damage are directly linked with the sub-regions of variables. In this study, the variables with the top six Q values identified by the segment-based factor detector are used as examples for illustrating the risk distributions of pavement infrastructure performance. The six values include total masses of vehicles, soil deep drainage, percentage of heavy vehicle mass, total volumes of vehicles, soil type and annual precipitation. The six variables have the largest relative contributions ($Q > 0.1$) and they are included in 18 of the top 20 interactions. Figure 5-13 shows the levels of risks within sub-regions of variables and the corresponding spatial distributions at high or low risks. For instance, road segments with very high risk associated with the total masses of vehicles are primarily located at the southern part of Brand Highway. Road segments of high risk are located at Brand Highway, Great Northern Highway, Great Eastern Highway and Albany Highway, and other road segments are at low risk. For the sub-regions determined by soil deep drainage, road segments at very high risk are primarily on Brand Highway, and those at very low risk are distributed on the southern part of Great Northern Highway, western part of Great Eastern Highway, and Albany Highway.

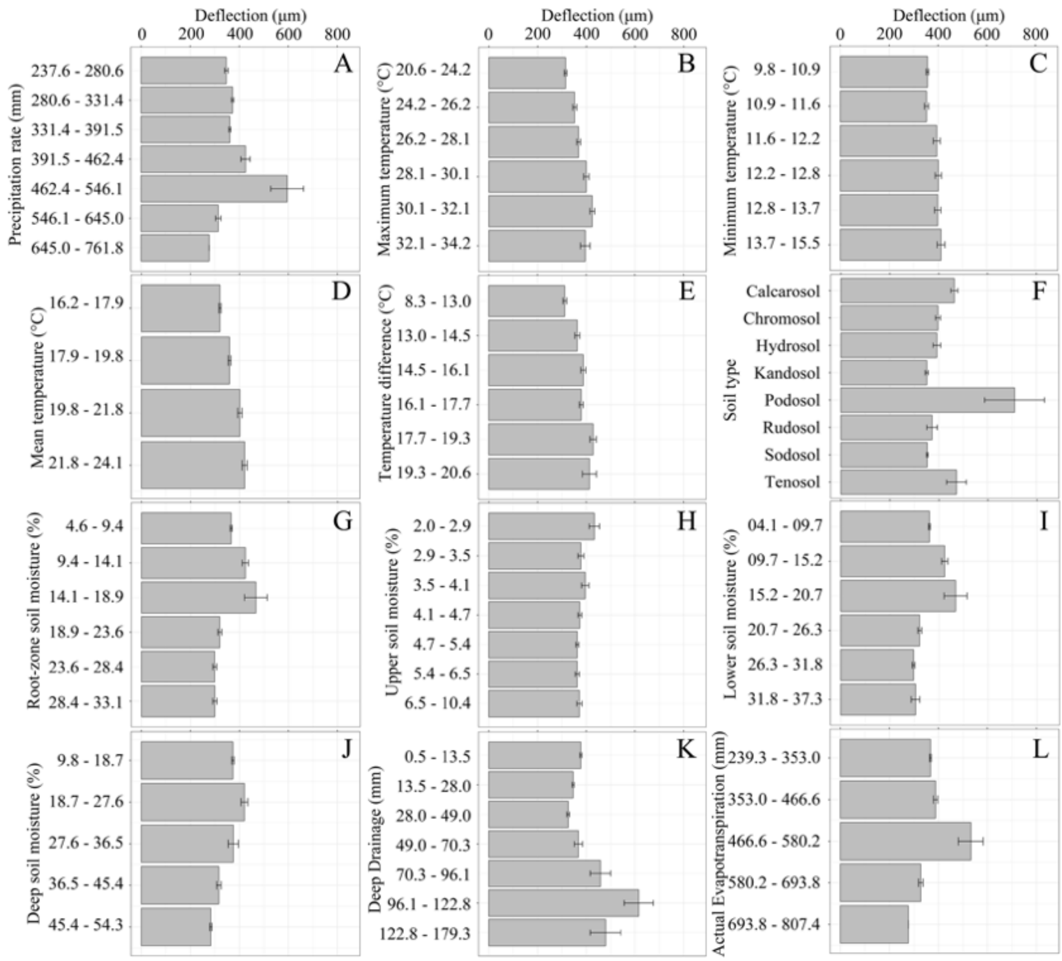

Figure 5-10. Levels of risk within sub-regions of variables within the category of climate and environmental factors

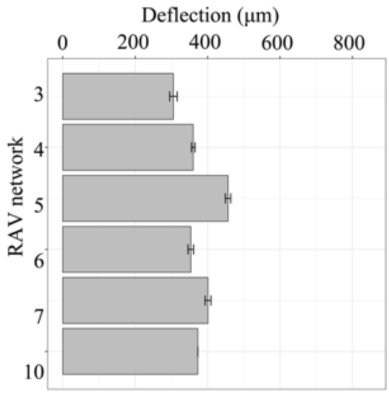

Figure 5-11. Levels of risk within sub-regions of variables within the category of road characteristics

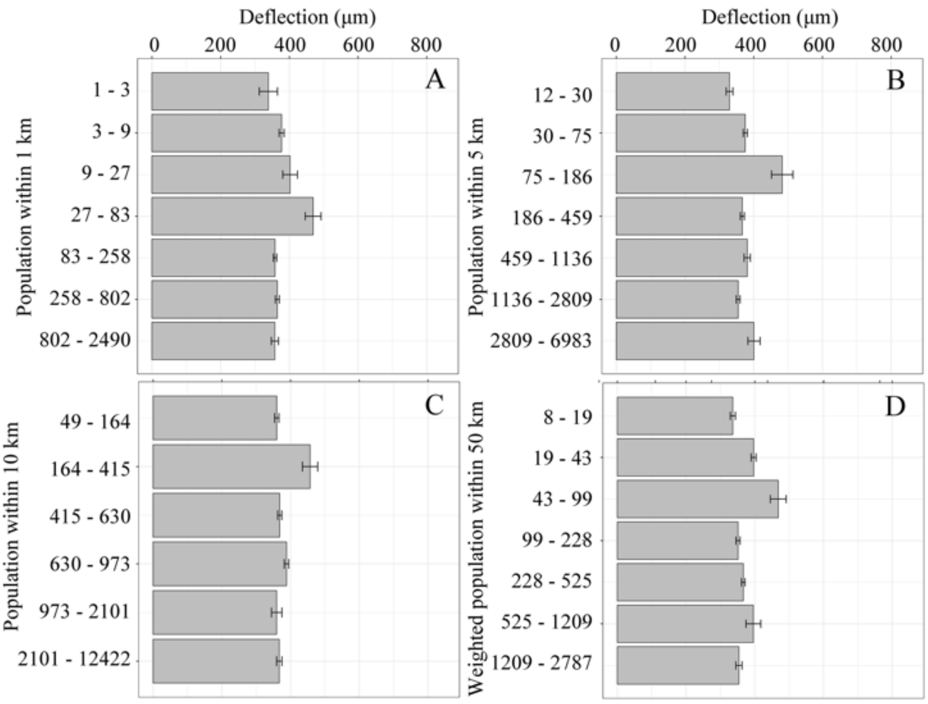

Figure 5-12. Level of risks within sub-regions of variables within the category of socioeconomic factors

Table 5-4. Definitions and descriptions of pavement infrastructure performance risk levels.

Level of risk	Description
Very high risk	Road segments within the sub-region of the highest risk of pavement deflections.
High risk	Road segments within the sub-region of the second highest risk of pavement deflections.
Medium risk	Road segments within the sub-regions of median risks of pavement deflections, and outside of other levels of risks.
Low risk	Road segments within the sub-region of the second lowest risk of pavement deflections.

Very low risk	Road segments within the sub-region of the lowest risk of pavement deflections.

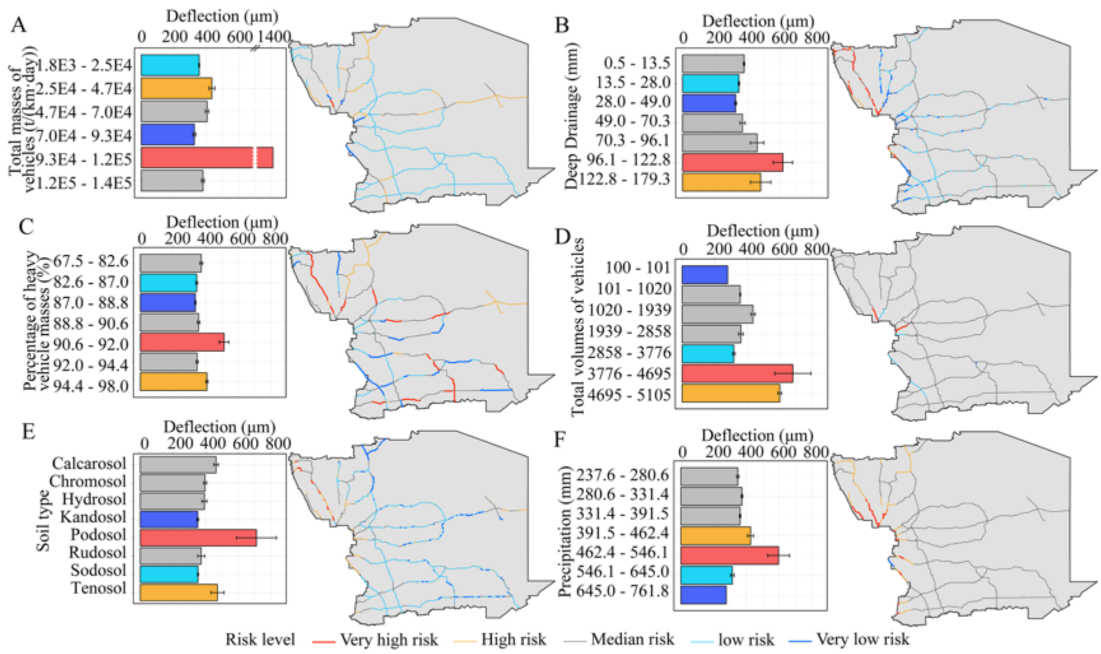

Figure 5-13. Levels of risks within sub-regions of variables with top six Q values and the corresponding spatial distributions of pavement performance at high or low risks

5.5 Discussion

5.5.1 The segment-based spatial stratified heterogeneity analysis

Compared with traditional point or area based geographical observations, segment-based observations have specific geometric and heterogeneity characteristics. In previous studies, only a few segment-based spatial analysis methods were used for processing segment-based spatial data. Road and traffic data, such as pavement deflections, are typical segment-based observations, which are spatially homogeneous within a segment, but spatially heterogeneous on different segments across the road network (Song, Wang, et al. 2018). In this study, optimal discretization for segment-based pavement data and geographical detector are integrated in the segment-based spatial stratified heterogeneity analysis of exploring the impacts of potential variables on pavement infrastructure performance. This approach has the following innovations and advantages.

First, the geometric and heterogeneity characteristics of segment-based pavement data are included in the spatial stratified heterogeneity analysis. In general, spatial grids with certain sizes are applied on extracting response and explanatory variables from multi-source spatial data in a geographical detector. This method is reasonable and widely used in point and area based spatial observations (Cao, Ge, and Wang 2013, Wang et al. 2010). However, it is biased and unreasonable for segment-based data which are distributed along the line segments, such as road segments across the road network, due to the various and diverse shapes of line segments. If spatial grids are applied on segment-based data, the shapes and lengths within a spatial unit will be largely different, leading to biased inputs of spatial data and errors in the spatial analysis. In this study, the road network is segmented using the spatial unit of line segments with the same length, and values of spatial variables are summarized along the corresponding line segments. As a result, the spatial units of response and explanatory variables are identical across the road network. In addition, this method is applied on the scale effect analysis in optimal discretization for segment-based data to select the best length of line segments for segmenting the road network. By involving the geometric and heterogeneity characteristics of segment-based data, the optimal discretization processes can reflect the spatial patterns and characteristics of explanatory variables and the real conditions of pavement engineering.

In addition, to the best of our knowledge, this is the first study utilizing the geographical detector to address industrial and engineering problems. Results show that the segment-based geographical detector is suitable and practical in addressing industrial problems with line segment spatial data, such as assessing pavement infrastructure performance. The key reason is that no linear assumptions are required to both response and potential explanatory variables for the geographical detector in exploring their interrelationships (Wang et al. 2010). Meanwhile, both continuous and category spatial data can be used as explanatory variables in spatial stratified heterogeneity analysis, where continuous data are discretised. These characteristics of the geographical detector enable the wide prospects for its application on addressing industrial and engineering problems, and providing quantitative and accurate spatial analysis results for road maintenance decision-making.

Finally, the geographical detector provides various results at different levels. Exploration of potential variables and their spatially varied impacts on pavement infrastructure performance is critical for understanding current and historical conditions, and appropriate decision-making of road and transportation authorities. It is also a sophisticated issue associated with numerous factors that might have diverse impacts. In the segment-based geographical detector, the relative importance of potential variables is explained by the factor detector and the interactions between variables and between categories are revealed by the interaction detector. The road segments at high or low risk of pavement damage are identified using the risk detector. Thus, researchers and practitioners can use one or several models of geographical detector to address their own problems. Furthermore, comprehensive application of spatial analysis results at different levels is beneficial for an in-depth understanding of the mechanisms of how the factors can affect pavement infrastructure performance.

5.5.2 Comprehensive impacts of climate and heavy vehicles

There are three major findings in this study. Vehicles, especially heavy vehicles, and climate and environmental conditions, are two main categories of contributors to pavement damage. In general, engineers and road managers believe that vehicles are the primary contributors to road damage (Cebon 1988, Ede 2014). This study reveals the respective contributions of traffic volumes and vehicle mass. Results show that the vehicle masses have more influence than volumes on pavement infrastructure performance. The contributions of total mass of vehicles and percentage of heavy vehicle mass are 2.01 and 1.31 times the contributions of total volumes of vehicles and percentage of heavy vehicle volume, respectively. Similar results also appear in the relevant studies. For instance, vehicle mass has a cumulative effect on pavement damage (Ede 2014), and pavement maintenance costs lead by overloaded vehicles are twice the costs of the same vehicles within legal loads (Pais, Amorim, and Minhoto 2013). In addition, climate and environmental conditions are usually assumed to be constant in the current and past pavement design and maintenance, but they actually vary at different times and across space. This study indicates that the impacts of climate and environment are significant and the impacts vary on different road segments on the road network. Static assumptions of climate and environmental conditions may result in premature deterioration of pavements (Li, Mills, and McNeil 2011). This study also presents that different variables of climate and environmental conditions have relatively different negative impacts on the pavement. Previous studies mainly focus on the impacts of temperature on pavement damage (Chinowsky, Price, and Neumann 2013, Chinowsky et al. 2013, Neumann et al. 2015, Byram et al. 2012, Qiao et al. 2013). For instance, it is estimated that warming temperatures will probably lead to US$13.6, US$19.0 and US$21.8 billion additional costs for pavement maintenance by 2010, 2040 and 2070 under RCP4.5 future climate change scenarios in the US (Underwood et al. 2017). In some regions that use asphalt pavements, pavement service life will be significantly reduced due to the increased temperatures and pavement designs that are not adapted to climate change (Qiao et al. 2013). However, this study shows that the impacts of different indicators, including soil moisture, soil type and precipitation are much greater than the impacts of temperature. Pavements are generally temperature sensitive, but the degrees are different due to various types of pavements and diverse surrounding environment. In the Wheatbelt region, the impacts of traffic masses and soil moisture are much higher than impacts of temperature on the pavement performance. For temperature variables, mean temperature along road segments is more important than the maximum temperature, minimum temperature and temperature difference. While the impacts from soil deep drainage, soil type and precipitation are 6.24, 4.76 and 4.48 times of the impacts of mean temperature, these factors were seldom considered in previous studies.

In addition, variables of vehicles and heavy vehicles in particular and climate and environmental conditions have significant interactive influence on pavement infrastructure performance. The impacts from the interactions can explain more than half of the pavement damage. Only a few previous studies investigated the interactive or combined impacts of vehicles and climate on pavements, even though multiple variables are used for the prediction of pavement performance (Bianchini and Bandini 2010, Marcelino, Lurdes Antunes, and Fortunato 2018). For example, experiments performed in Guangzhou, China, indicate that the dynamic behaviours of asphalt pavement structure are largely affected by the coupled loads of different temperature and vehicle masses using a coupling dynamic model (Xue et al. 2013). In this study, the interactions between different variables of vehicles and climate are explored and discussed in detail. From the perspective of relative importance measured by Q value, multiple interactions between the category of vehicles and heavy vehicles, and climate and environment, can explain more than half of the pavement damage. The interactions between percentage of heavy vehicle mass and soil type, soil deep drainage, and precipitation, can explain 56.6%, 52.5% and 50.5% of pavement deflections respectively. The interaction between the total mass of vehicles and soil deep drainage explains 54.4% of pavement deflections. The interactions between the percentage of heavy vehicle volume and precipitation, and actual evapotranspiration, explain 53.5% and 51.6% of pavement deflections in the Wheatbelt. Meanwhile, this study shows that the interactions between vehicles and the percentage of heavy vehicles also make significant contributions to pavement damage. The interaction between total volume of vehicles and percentage of heavy vehicle volume, and the interaction between total masses of vehicles and percentage of heavy vehicle mass account for 54.3% and 53.2% of pavement deflections, respectively.

Finally, the impacts of the above two categories of variables are also linked with the local socioeconomic conditions, such as populations that reflect the usage of local road segments. Segment-based spatial stratified heterogeneity analysis reveals that the weighted population within 50 km of road segments contributes to 6.4% of pavement deflection, and its interaction with precipitation can explain 45.3% of pavement deflection. The interaction between population within 1 km of road segments and percentage of heavy vehicle mass explains 40.7% of pavement deflection. Growing population usually leads to multiplied vehicles on the roads and can sharply increase the necessity for freight transportation, which have cumulative impacts on pavement damage (Ede 2014). Thus, socioeconomic factors are effective supplements for vehicles and climate variables for explaining the sophisticated problems of pavement damage.

5.5.3 Practical recommendations

Based on the spatial analysis results, this study has the following practical recommendations for optimizing and improving pavement design, management, construction and maintenance practices. First, for the design and construction of new roads, data-driven analysis of potential pavement performance should be assessed in terms of the surrounding climate, environment and socio-economic conditions to design the road pavement, such as the pavement service life, materials and thickness of asphalt concrete overlay (Wang 2012, Wen et al. 2017). The quantitative and accurate assessment of pavement performance can avoid underestimation of the burden of road maintenance and overestimation of pavement service life. Next, more attention should be paid to the impacts of climate and surrounding environmental conditions on pavement performance. In general road management and pavement engineering practices, traffic volumes especially the masses of heavy vehicles are regarded as the primary source of pavement damage (Song, Wang, et al. 2018). In this study, the spatial segment-based stratified heterogeneity analysis indicates that the contributions of climate and environmental factors are as high as the impacts of vehicles, and they have nonlinearly enhanced interactive impacts on the pavement. Finally, spatial difference needs to be involved in the whole life-cycle of road pavement. The performance of pavement and its factors are significantly varied across the road network. The spatially local identification of pavement performance and the factors benefit for the more accurate and reasonable decision-makings for reducing the impacts of factors and resurfacing costs, and prolonging pavement life.

5.5.4 Recommendations for future research

Even though this study demonstrates the contributions of vehicles and heavy vehicles, climate and environment, socioeconomic factors and the characteristics of roads, and their interactions on pavement damage, more investigations are still required in the future research. Assessing the comprehensive impacts of multi-source factors on pavement infrastructure performance has been a key research area for researchers, engineers and managers since the 1930s (Main Roads Western Australia 1996). In Australia, 12.9 million dollars was spent in 2015-16 on the 24-year long Austroads Long Term Pavement Performance Program (Austroads Ltd. 2016). In this research, several recommendations are proposed for future research about understanding factors of pavement infrastructure performance. From the perspective of methodology, prediction methods can be considered for spatial stratified heterogeneity analysis, so that future scenarios of pavement infrastructure performance can be predicted based on historical data, which is one of the most important sources of evidence for decision-making of predictive road maintenance. From the perspective of data, more variables can be monitored, collected and analysed, such as adverse and extreme weather condition data. Studies in other regions are also necessary to reflect the local pavement conditions and potential factors.

5.6 Conclusions

Road infrastructure is important to the well-being and economic health of all nations. Comprehensive understanding of the impacts of climate and heavy vehicles on pavement infrastructure performance is critical and necessary for road infrastructure maintenance and management. The performance of pavement infrastructure is sophisticated and affected by numerous factors and varies greatly across different roads. This study explores the comprehensive impacts of vehicles and heavy vehicles, climate and environment, road characteristics and socioeconomic conditions on pavement infrastructure performance with spatial stratified heterogeneity of segment-based variables. Different from point and area geographical observation data, indicators of pavement performance are segment data distributed along road segments of the road network. Segment-based optimal discretization is used to discretise segment-based pavement data on the road network and applied on segment-based geographical detector. This approach provides new ideas for spatial analysis of segment geographical data. Spatial analysis reveals that vehicles and climate variables are the major factors associated with pavement damage, where the variables having the largest relative importance include total masses of vehicles, soil deep drainage, percentage of heavy vehicle mass, total volume of vehicles, soil type and precipitation. Vehicle masses have more influence than volumes. The contributions of total mass of vehicles and percentage of heavy vehicle mass are 2.01 and 1.31 times the contributions of total volumes of vehicles and percentage of heavy vehicle volume, respectively. Meanwhile, the impacts from soil deep drainage, soil type and precipitation are 6.24, 4.76 and 4.48 times the impacts of mean temperature on pavement damage, but these factors are rarely considered. Instead, temperature has been commonly used as an indicator of climate in previous studies. In this research, soil and precipitation have more influence than temperature, which may be linked with the temperature insensitive pavements on some roads in the Wheatbelt region. The interactions between variables of vehicles and heavy vehicles and variables of climate and environmental conditions have significant influence on pavement infrastructure performance, which can explain more than half of the pavement damage. Socioeconomic conditions also have impacts on pavement performance to some extent, but the impacts of road characteristics are limited. The methodology in this study can objectively reveal the spatial associations between pavement performance and explanatory variables. Nowadays pavement practices in developed countries focus more on maintenance and renewal. The findings provide quantitative contributions of variables on pavement performance, so the variations of pavement performance that are affected by variables needs to be considered in the practical decision-making for road design, construction and maintenance.

Chapter 6 Geospatial Multi-Criteria Decision Making for Road and Heavy Vehicles Management

6.1 Introduction

In this chapter, to more comprehensively investigate the overall performance of road infrastructure and to determine a more accurate performance measure, a model-driven fuzzy spatial multi-criteria decision making (MFSD) is utilized for indicator selection and for deriving an overall indicator. The MFSD method integrates model-driven decision making, multi-criteria decision making (MCDM), fuzzy set theory, and geographical information systems (GIS), and can both generate an overall indicator and support decision making. First, the MFSD method is developed based on MCDM, so it is used to select proper alternative indicators, where the factors affecting the indicators are taken into account for decisions. The analytic hierarchy process (AHP) is used to obtain weights of alternatives, and AHP and the technique for order of preference by similarity to ideal solution (TOPSIS) are comparatively applied in assessing the alternatives performance indicators. Second, the MFSD method is a model-driven decision-making method that replaces expert opinion in traditional decision making by data and models, such as statistical models, machine learning algorithms and spatial analysis models, to reduce the potential biases and uncertainties of linguistic descriptions. Third, fuzzy set theory is applied for modelling sophisticated systems that cannot be defined with exact numbers using membership functions. Finally, GIS is combined with the decision-making processes to integrate both spatial and aspatial data to identify alternative indicators and calculate a decision matrix of alternative indicators and factors. In this research, the methods are used to address road decision issues about the road network in the Wheatbelt in WA, Australia. The segment-based spatial data of four monitored pavement indicators, including deflection, curvature, roughness and rutting, are collected for quantifying road infrastructure performance. Correspondingly, three categories of spatial variables (road properties, traffic vehicles and climate conditions), are derived from multi-source data and summarized to the spatial unit of road segment.

6.2 Study area and data

6.2.1 Study area and alternatives

Road freight transportation is one of the primary modes of transport in Australia. The freight moved by road shares 52% of tonnages moved and 42% of the whole ton-kilometres travelled among the road, rail, sea and air networks in Australia (Australian Bureau of Statitics ABS 2002). Main roads in WA, represent "one of the world's most expensive road networks", whose performance is continuously improved to meet the requirements of community, industry and other stakeholders (Main Roads Western Australia 2018b). WA undertakes approximately one third of the total ton-kilometres of freight transportation of eight states and territories in Australia (Australian Bureau of Statitics ABS 2002). The primary contributors of the freight transportation are long-distance movements of heavy commodities, including mining (e.g. iron ore) and agricultural products (e.g. grain, beef and lamb). The Wheatbelt region plays a critical role in road freight transportation in WA, since it links the Perth Metropolitan region, the capital city of WA, and the mining and agricultural production regions (Figure 6-1). The Perth Metropolitan region is on the coast to the west of the Wheatbelt region, and there is a huge demand for industrial production and living materials. For instance, more than 78% of the population in WA live in the Perth Metropolitan region, and the total port trade including both imports and exports in Fremantle Port in Perth Metropolitan region reached 35.3 million tons in 2017 (Fremantle Ports Australia 2018). Meanwhile, the Wheatbelt region and its adjacent northern, eastern and southern regions are the grain, sheep, metal and non-metallic mineral production regions (Department of Transport Western Australia 2017). In addition, improving the road infrastructure performance is increasingly important for reducing traffic incidents and ensuring road safety in WA and the Wheatbelt region. Even though the WA traffic fatality rate is reduced by one third compared to a decade ago, the WA traffic fatality ratio of 0.074‰ is still higher than the Australian traffic fatality ratio of 0.054‰ in 2016 (Bureau of Infrastructure and Economics 2016). The Wheatbelt fatality rate reaches 49.8 per 100,000 people, which is about seven times the state rate and ten times the Australia national rate in 2014 (Government of Western Australia 2015). The Wheatbelt serious crash rate is also the highest among all regions in WA. Among the factors of serious crashes, the top two contributors in the Wheatbelt region, a single vehicle hitting an object (54%) and vehicle speed (16%), are higher than other regions (Government of Western Australia 2015). Thus, even though the traffic incidents are also associated with other factors, such as drink driving, the road and its surrounding environmental conditions are still the main contributors.

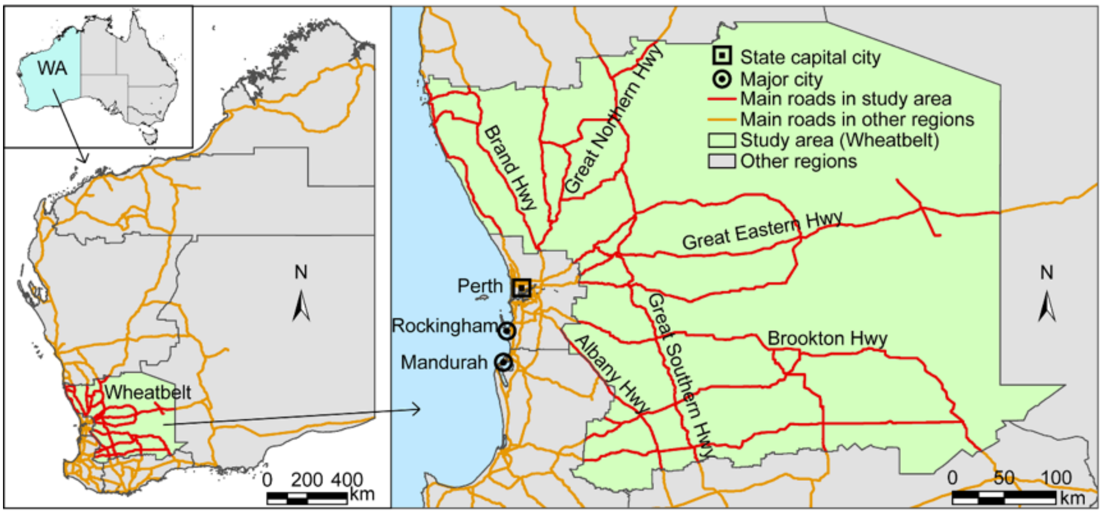

Figure 6-1. Study area and the main road network.

To describe the road infrastructure performance, four indicators of pavement conditions are monitored, including deflection, curvature, roughness and rutting (Figure 6-2). The data are collected by Main Roads WA with different length units along roads across the whole main road network in the Wheatbelt region. In the study, the main roads are spatially defined as 297 road segments in the road network, where road segments are parts of roads with similar construction, geographical and environmental conditions between junctions or intersections (Austroads 2016, Song, Wang, et al. 2018). Then, the values of four pavement performance indicators are spatially summarized to the road segment based spatial data. **Deflection** is a pavement strength indicator that is measured as the maximum depression of pavement surface under a standard load, and it is monitored using a Dynatest 8000 series Falling Weight Deflectometer (FWD) device and calibrated with Calibration Method WA 2060.5 by Main Roads WA (Main Roads Western Australia 2017a). The segment-based deflection ranges from 151 μm to 762 μm and the mean deflection is 368.8 μm in the study area. **Curvature** is an indicator of asphalt fatigue that represents the shape of deflected pavement surface caused by loads. The value of curvature equals the maximum deflection for a certain test point minus the deflection at this point when the test load is 200 mm from the test point where there is a maximum deflection. The segment-based curvature ranges from 43.7 mm to 237.6 mm with a mean of 132.1 mm in the Wheatbelt region. **Roughness**, measured with the International Roughness Index (IRI), can reflect road surface deviations of the longitudinal profile. The roughness conditions can affect vehicle dynamics, vehicle operating costs, driving comfort, and safety and pavement loading. In Australia, the acceptable maximum roughness values are determined by the road roughness acceptability functions, which present the comparison between the objective service quality levels, including the travel time cost and time, to practical levels of user satisfaction with service quality (Potter et al. 1992). In terms of the road strategic asset management plan in the Australian Capital Territory (ACT), the roughness of at least 88% of roads should be lower than 4.2 to satisfy the road performance target (Bureau of Infrastructure 2017). In this study, four road segments (8 km) have roughness higher than 4.2 among 297 road segments (3595 km) in the Wheatbelt region, which indicates that the Wheatbelt roughness performance is within the above recommended road asset management plan. It should be noted that the road roughness target varies in different places due to diverse road constructions and local environment. **Rutting** is an indicator of pavement surface and structural conditions and the potential aquaplaning problems. It is measured as the largest upright displacement of the road surface transverse profile (White 2002). In Australia, the maximum rutting of 20 mm is used as the intervention threshold for main roads (Smith, Cercina, and Peelgrane 1996, Fwa, Pasindu, and Ong 2011). In the Wheatbelt region, the maximum rutting within the spatial unit of a road segment is 10.1 mm, which means the rutting in all road segments are under the intervention level.

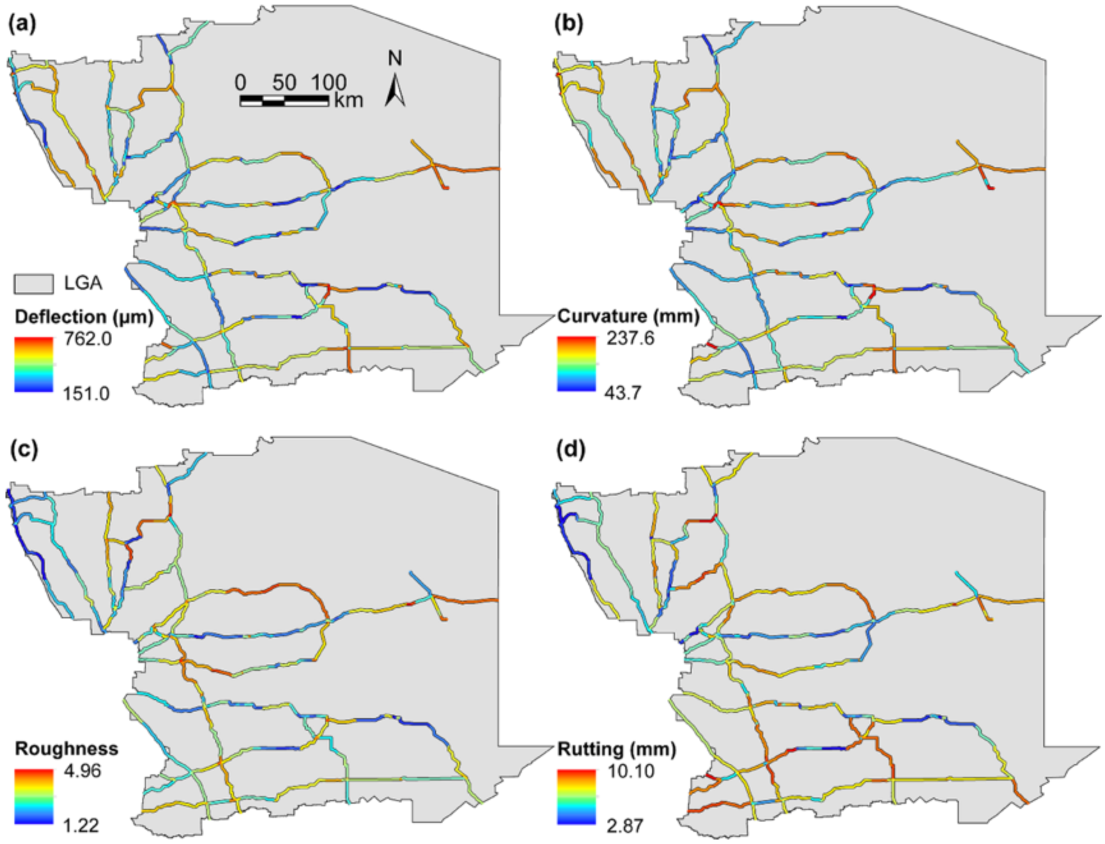

Figure 6-2. Spatial distributions of alternatives for assessing road conditions and road maintenance burden.

6.2.2 Explanatory variables of criteria

The explanatory variables of criteria are collected from three categories: properties of road, statistics of traffic vehicles, and local climate and environmental variables. The three categories of variables correspond to the three criteria: road, vehicles and climate. The spatial distributions of the raw data of the road, vehicles and climate explanatory variables are presented in Figures 6-3, 6-4 and 6-5, respectively. Then the variables are pre-processed and summarized to the segment-based data with the consistent spatial unit (road segment) of road performance indicators. Table 6-1 lists the segment-based spatial data of criteria explanatory variables. The brief descriptions and data sources of the three categories of explanatory variables are introduced in the following paragraphs.

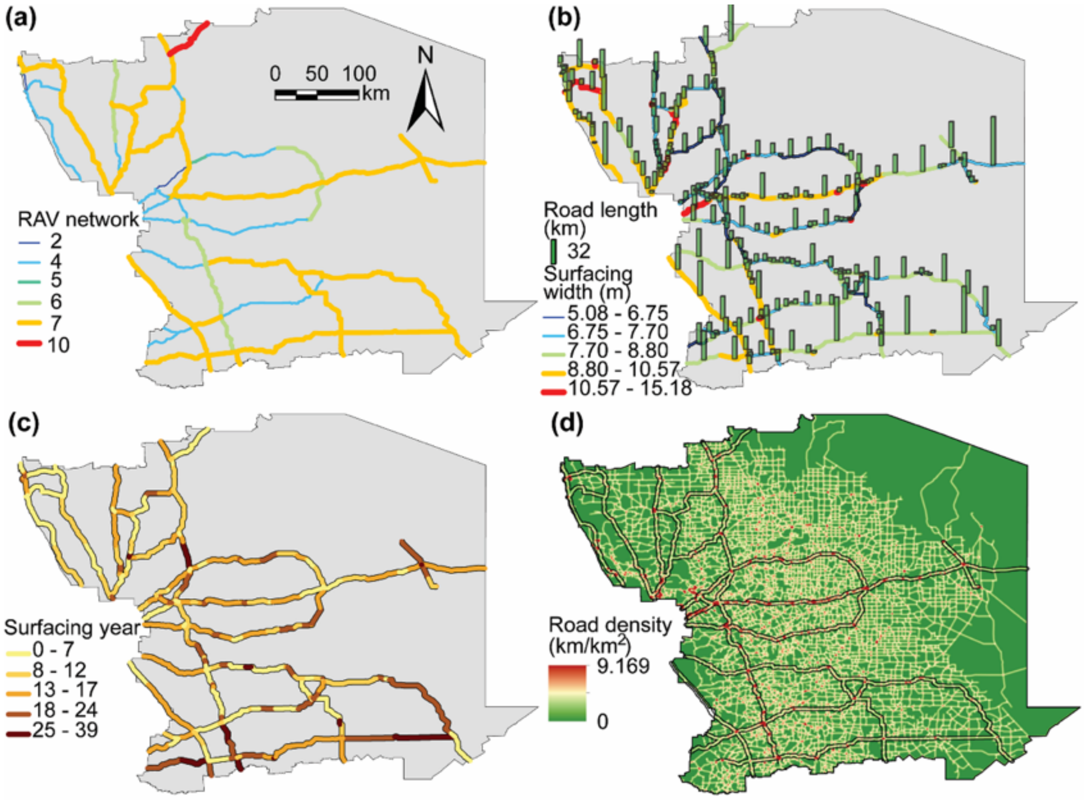

Figure 6-3. Spatial distributions of variables of road characteristics.

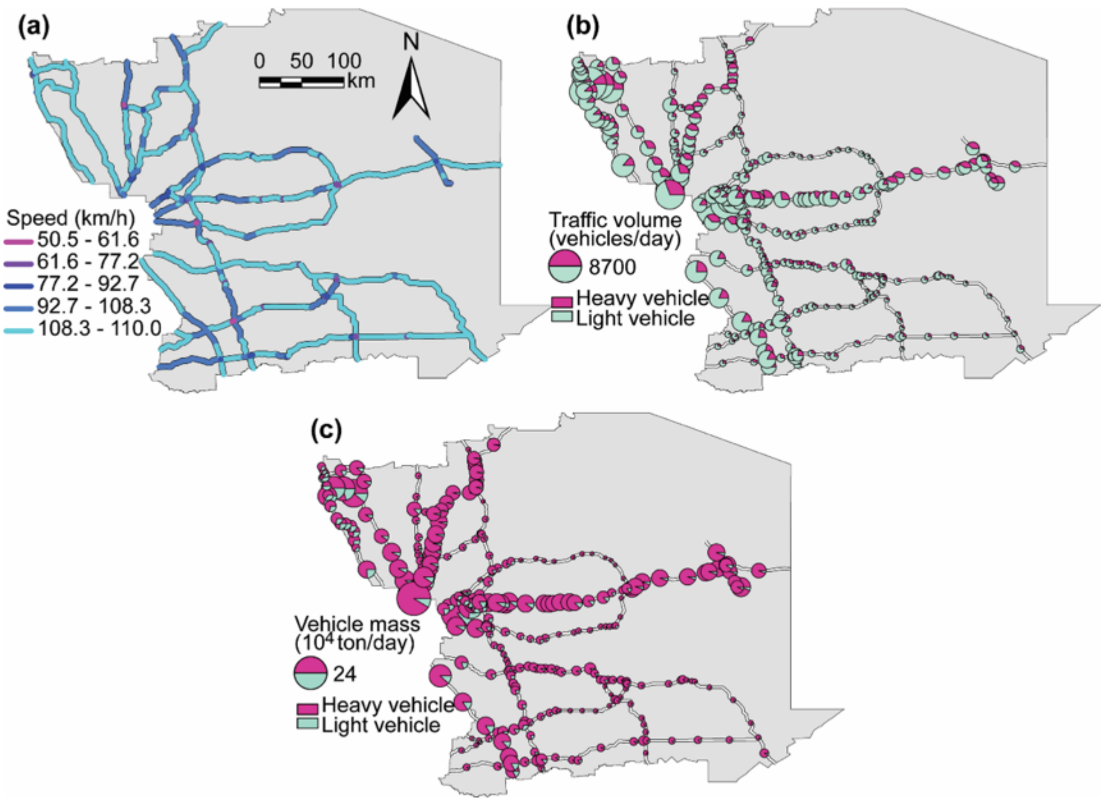

Figure 6-4. Spatial distributions of variables of vehicles and traffic conditions.

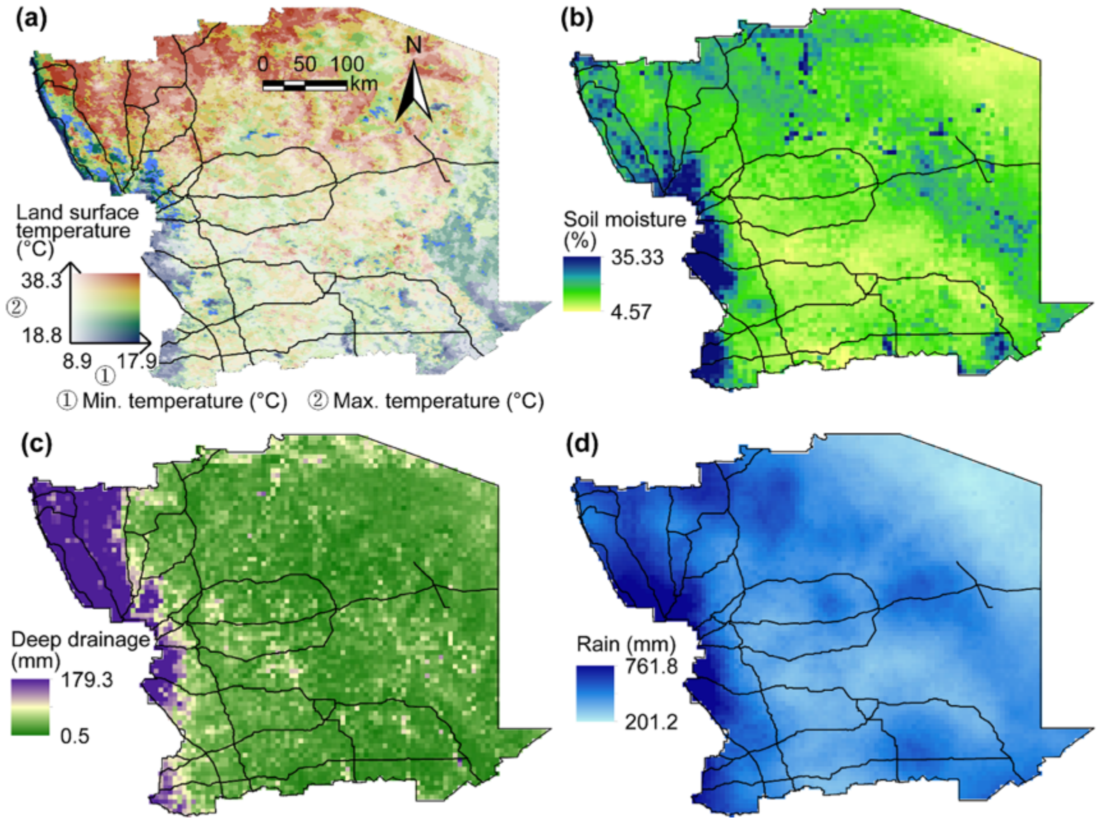

Figure 6-5. Spatial distributions of variables of climate and environmental conditions.

Table 6-1. Summary of segment-based spatial data of explanatory variables of criteria

Criteria/ Category of variable	Sub-criteria/ Variable	Code of variable	Min	Max	Mean
Road	RAV network	ravnw	2	10	5.9
	Road length (km)	length	0.8	64.2	12.1
	Surfacing width (m)	surfwidth	5.1	15.2	8.3
	Surfacing year (to 2015)	surfyear	0	39	12.2
	Road density (km/km^2)	roaddens	0.5	8	1.4
Vehicles	Traffic speed (km/h)	speed	50.8	110	100.6
	Volume of heavy vehicles (vehicles/day)	vlmhv	30.1	2133.7	253.7
	Volume of light vehicles (vehicles/day)	vlmli	105.4	8565.8	876

	Volume of total vehicles (vehicles/day)	vlmtt	136.3	9525.3	1129.7
	Mass of heavy vehicles (10^4 ton/day)	masshv	0.26	22.94	2.55
	Mass of light vehicles (10^4 ton/day)	massli	0.05	3.85	0.39
	Mass of total vehicles (10^4 ton/day)	masstt	0.37	25.1	2.95
	Percentage of heavy vehicle volumes (%)	pcthv	7.4	54.5	23.7
	Percentage of heavy vehicle masses (%)	masspcthv	51.8	97.1	84.5
Climate	Annual average daily minimum temperature (°C)	tmin	3.15	10.34	5.68
	Annual average daily maximum temperature (°C)	tmax	31.86	49.09	42.83
	Annual average daily mean temperature (°C)	tmean	19.18	28.37	24.26
	Annual average daily temperature difference (°C)	tdif	22.57	43.16	37.15
	Soil moisture (%)	sm	4.9	28.7	9
	Deep drainage (mm)	dd	2.3	135.4	25.9
	Annual rainfall (mm)	rain	250.9	681.2	341

The road performance variables are used to describe the road functional properties, geographical and geospatial characteristics, and the surfacing information of pavements. RAV networks classify roads based on the maximum permitted size and mass of heavy vehicles, including number of axle groups, length and height (Main Roads Western Australia 2016b). It is used to guide vehicles to access appropriate roads. Only vehicles with the loads and sizes lower than the regulated standards can access the roads of RAV network. Road length is the length of the central line of a road segment. Surfacing width is the average width of the pavement surface of a road segment. Surfacing year is the age of latest pavement surface until 2015. For instance, if the latest surfacing of pavement is 2000, then the surfacing year is 15. Road density is calculated using a kernel density function with both local roads and main roads to present the density of roads connected to and near the segments of main roads. The spatial data of main roads and local roads are provided by Main Roads WA and shared by Western Australian Land Information Authority (Main Roads Western Australia 2018a).

The variables of criteria vehicles indicate the traffic conditions and the roles of different types of vehicles on the road network. Traffic speed of road segments are summarized based on the legal speed limits that are used to regulate the speed of road vehicles in WA (Main Roads Western Australia 2017d). Traffic volumes, including the volumes of heavy, light and total vehicles, are the annual average daily traffic data monitored by Main Roads WA, and shared on the data port of Western Australian Land Information Authority (Main Roads Western Australia 2018b). The traffic volumes on the road segments without observations are predicted using a segment-based regression kriging (SRK) method. The SRK method can more accurately predict traffic conditions compared with point-based spatial prediction methods due to the integration of the information of segment-based spatial data and the regression kriging method using a segment-based spatial covariance function (Song, Wang, et al. 2018). The SRK method is performed using the *SK* R package (Song 2018b). Then, the traffic masses on road segments, including the masses of heavy, light and total vehicles, and the percentages of heavy vehicle volumes and masses are computed based on the predicted traffic volumes.

The climate criteria variables reveal the local climate and environmental conditions along and around the road segments. The climate variables include temperature variables, soil moisture, soil deep drainage and annual rainfall. The temperature data are the day-time and night-time temperatures sourced from 1-km resolution 8-Day L3 Global Land Surface Temperature (LST) and Emissivity product (MOD11A2) from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Wan, Hook, and Hulley 2015). The temperature data are then processed to the temperature variables, including annual average daily maximum, minimum and mean temperatures, and temperature difference. The soil moisture, deep drainage and annual rainfall data with spatial resolution of 5 km are sourced from soil moisture data products provided by the Bureau of Meteorology, Australia (Bureau of Meteorology Australian Government 2017). Similar to the road and vehicles criteria variables, the climate data are also summarized to the segment-based spatial variables for the spatially corresponding roads.

6.3 Model-based fuzzy spatial multi-criteria decision-making (MFSD) method

The MFSD method is a decision making method integrating MCDM, GIS, fuzzy theory and model-based decision making. The MFSD method includes the following five steps. (1) Select criteria and variables and pre-process data using exploratory data analysis methods. This step is introduced in Section 6.3.1. (2) Compute contributions of criteria and variables on alternatives based on multiple models, which include statistical models, machine learning algorithms and spatial analysis models in this study. This step is introduced in Section 6.3.2. (3) Use fuzzy set theory to calculate fuzzy membership functions of criteria variables to quantify their relative importance and weights based on the model-based contributions of criteria. The fuzzy set theory and fuzzy extent analysis are presented in Section 6.3.3. (4) Apply fuzzy MCDM in computing an indicator with the weighted criteria and decision making for ranking alternatives. The mathematical concepts and processes of fuzzy analytical hierarchy process (FAHP) and fuzzy technique for order preference by similarity of an ideal solution (FTOPSIS) are presented in Section 6.3.4 and 6.3.5 respectively. The process of MFSD-based indicator for mapping road maintenance burden is presented in Section 3.6. The MFSD-based decision making for ranking alternatives of road performance indicators is presented in Section 6.3.7. (5) Analyse sensitivity of MFSD-based decision making due to the input parameters, which is presented in Section 3.7.

6.3.1 Criteria selection and data pre-processing

The selection of criteria consists of two parts. First, collect data of potential variables of criteria. The principle of criteria selection is that they should reasonably represent and contribute to the final objective, which is to describe the overall road infrastructure performance and the burden of road maintenance in this thesis. In the study, spatial data of three criteria, including road, vehicles and climate, and 21 sub-criteria are collected as shown in Section 6.2.2. To ensure consistent spatial units with the road performance indicators, the criteria data are all processed and summarized as segment-based spatial data.

Once the datasets are collected, variables should be normalized to the range [0, 1] to eliminate the impacts of different units and scales of variables. The normalization function of a variable var is:

$$f(var) = \frac{X - \min(var)}{\max(var) - \min(var)} \tag{6-1}$$

or

$$f(var) = \frac{\max(var) - var}{\max(var) - \min(var)} \tag{6-2}$$

where equation (6-1) is for positively related variables and equation (6-2) is for the negatively related variables associated with the study objective.

Second, select statistically correlated variables with alternatives to eliminate variables without significant correlations. The process of variable selection in this step is determined in terms of the models for computing contributions of criteria. For the statistical models, machine learning algorithms and spatial regression models, one of the following two techniques to select variables is recommended. One method is the combination of correlation analysis and multi-collinearity analysis. If the variables are normally distributed, the Pearson correlation can be used for correlation analysis; if they are not normally distributed, the Spearman correlation is recommended (Heuvelink 1998, Ge, Song, et al. 2017). The collinearities among variables can be diagnosed using the variance inflation factors (VIFs). In general, a variable should be removed when VIF is higher than 4 due to its significant collinearity with other variables. Another approach for variable selection is step-wise linear regression. The main idea of step-wise linear regression is that the regression model is built from a set of candidate explanatory variables through entering and removing variables in the model in a step-wise manner until no entering and removing are required (Bendel and Afifi 1977).

6.3.2 Model-based contributions of criteria

In the MFSD approach, criteria contributions to objectives are computed with a series of models instead of experts or decision makers. In this study, the contribution computation models include 11 models in three categories: statistical models, machine learning algorithms and spatial models (Table 6-2). For all models, the criteria data should be pre-processed and the variables should be selected through the two steps mentioned in Section 6.3.1. Optionally, if all the selected variables are theoretically associated with the objective and alternatives, the variables with statistically significant correlations with alternatives are not required for a few models, such as ridge regression and geographical detectors, since they can avoid the impacts of variables that are not significantly correlated with alternatives. The brief descriptions and mathematical processes for computing contributions of criteria of the three categories of models are presented in the following three paragraphs.

Table 6-2. List of models used for computing contributions of criteria

Category of models	Model	Code
Statistical models	Correlation analysis	correlation
	Step-wise linear regression	steplm
	Ridge regression	ridger
	Generalized additive model (GAM)	GAM
Machine learning algorithms	Artificial neural network (ANN)	ANN
	Support vector machine (SVM)	SVM
	Regression tree (RT)	RT
	Random forest (RF)	RF
Spatial models	Geospatial generalized additive model (GeoGAM)	GeoGAM
	Geographically weighted regression (GWR)	GWR
	Geographical detectors (GD)	GD

Statistical models for criteria contributions calculation include correlation analysis, step-wise linear regression, ridge regression and generalized additive model (GAM). The mathematical theories of the four models are distinct and can reflect different aspects of data. **Correlation analysis** examines the contributions of variables to alternatives by correlation coefficient and the corresponding significance level. In general, the range of correlation coefficient is [-1, 1], where a larger absolute value means a stronger correlation. The value of the correlation coefficient does not fully reflect the extent of correlation because of the degree of freedom, so the corresponding significance level should be considered (e.g. 0.05). In this study, the Pearson correlation is used since the four alternative road performance indicators are all normally distributed. **Step-wise linear regression** regresses multiple variables and removes explanatory variables that are not significantly correlated with response variables simultaneously. **Ridge regression** is a robust regression method that can avoid overfitting and multi-collinearity without removing predictor variables (Hoerl and Kennard 1970, Marquaridt 1970). The R *glmnet* package is used for the computation of ridge regression, where cross validation is utilized to determine tuning parameters that control the penalty term strength (Friedman, Hastie, and Tibshirani 2010). **GAM** is a widely used nonlinear regression model. In GAM, the nonlinear relationships between responses and explanatory variables are described via nonparametric smoothing functions (Hastie and Tibshirani 1990). The R *mgcv* package is used for GAM calculation (Wood 2017, 2003). The parameters of smoothing functions are automatically determined through the iteration of the generalized cross validation (GCV) criterion, which has benefits for the improvement of computation efficiency and the assessment of impacts of variables on GCV scores (Wood 2006, Song et al. 2015).

Machine learning algorithms used in the study are support vector machine (SVM), artificial neural network (ANN), regression tree (RT) and random forest (RF). The four models can be used for both classification and regression, and they are used for regression in this study. They are different from statistical linear or nonlinear regression in that the forms of functions are pre-specified, the four models have the assumptions of relationship functions. Due to the complex nonlinearity and relatively high fitness of machine learning models, strict statistical variable selection and multi-collinearity analysis are required before modelling to avoid overfitting. In **ANN** models, the learning process is performed through massive interconnected artificial neurons and weighted links among elements and outcomes (Lek and Guégan 1999, Schalkoff 1997). The information flows in a single direction through hidden layers from input layers to output layers. Then, the best solution is identified in terms of network complexity of the adaptive learning and the support of explanatory variables. The ANN analysis is performed with R *nnet* package (Venables and Ripley 2002). The ANN model is run 100 times and use the mean overall fitness and relative importance of variables to calculate the reliable contributions of criteria. In **SVM** for regression or support vector regression (SVR), to determine the best regression function, a hyperplane is constructed to maximize the margin and to minimize the regression error, where margin is the distance between hyperplane to the closest neighbour point (Drucker et al. 1997). Similar to the ANN model, the SVM model is run 100 times to derive the reliable contributions of criteria, and it is performed by the R *rminer* package (Cortez 2010). **RT** constructs a series of rules for explanatory variables and recursively divides data into ordered subsets with binary splits in terms of each explanatory variable (Breheny 1984, Breiman 2017). Then, the best split is selected through a thorough search and assessment of splits of all variables. In general, the split with maximum homogeneity regarding response variable is selected. The RT model is run by R *rpart* package (Therneau, Atkinson, and Ripley 2018). **RF** builds massive decision trees for training data and regresses with average predictions of individual trees (Ho 1995, Barandiaran 1998). The trees grow from randomly selected sub-groups of variables of split parts, and they can grow without trim. The trees grow independently to the maximum size sampling from a bootstrap of training, then remaining samples are used for calculating the unbiased out-of-bag error rate and the relative importance of variables (Breiman 2001, Prasad, Iverson, and Liaw 2006). RF is robust to noise in data, overfitting problems and small sample sizes, and requires minimal manual parameterization. The RF analysis is run with the R *randomForest* package (Liaw and Wiener 2002). The above four models can provide an overall contribution and the respective relative importance of variables in the models. The contribution of variable x_i $(i = 1, \dots, n)$ is computed using the equation:

$$\beta_i = \beta_0 \cdot \frac{r_i}{\sum_i r_i} \tag{6-3}$$

where β_i is the contribution of variable x_i, β_0 indicates the overall contribution of selected variables, and r_i presents relative importance of variable x_i.

Spatial analysis models consist of geospatial generalized additive model (GeoGAM), geographically weighted regression (GWR) and geographical detectors (GD). **GeoGAM** is an extension of GAM, and integrates geographic information in the nonlinear regression models to describe spatial heterogeneity that is not presented by the explanatory variables (Kneib, Hothorn, and Tutz 2009, Fahrmeir et al. 2007). The geographic information might be the residence address, local statistical area (e.g.

block and village), county and location. In this study, GeoGAM is coded based on the GAM run by R *mgcv* package (Wood 2017, 2003). **GWR** is a critical local method to investigate geospatial non-stationarity of data relationships (Fotheringham, Charlton, and Brunsdon 1998). Different from aspatial regression models, such as linear regression, GWR enables locally varied regression parameters through location-wise estimation for each spatial variable (McMillen 2004, Fotheringham, Brunsdon, and Charlton 2003, Fotheringham 2000). In this study, the contributions of variables are calculated with the total fitness of the GWR model and the mean local coefficients of variables. **GD** is a spatial statistical model for analysing spatial relationships of variable with spatial variance and geographical strata (Wang et al. 2010). Since the contributions of variables are fully determined by the variance and geographical strata, no linear assumptions and collinearity test are required for a single variable and pairs of variables (Wang 2017). In this study, GD model is run by the R *GD* package (Song 2018a).

6.3.3 Fuzzy set theory

In this research, fuzzy set theory is integrated in decision making to involve the criteria contribution analysis from various models in this study. Fuzzy set theory is widely applied in complex system modelling that cannot be comprehensively described by crisp numbers or crisp boundaries. Fuzzy logic allows vague and ambiguous information in the input (Kaya and Kahraman 2010). Fuzzy sets theory uses membership functions to describe the preference of the attributes of interest (Chang 1996). Its application in spatial decision making usually utilizes membership functions where the values range in [0, 1] to present the degree of membership of variables (Jelokhani-Niaraki and Malczewski 2015). In this study, fuzzy set theory is used to compute model-based criteria contributions to reduce the inherent differences of contributions from various models, even though they tend to be consistent and similar. During decision making processes, fuzzy set theory can enable pairwise comparison of criteria and alternatives under different criteria.

In a study data space R, the fuzzy set Φ is presented as a set of data pairs:

$$\Phi = \{var, \mu_{\Phi}(var)\}, var \in R \tag{6-4}$$

where μ_{Φ} is the membership function, which presents the degree of membership of fuzzy set Φ to the data space R (Chang 1996). The fuzzy number M is presented as a triangular fuzzy number, and its function is denoted by (l, m, u), where $l \leq m \leq u$, and they indicate the lower, most possible and upper values, respectively (Kahraman, Cebeci, and Ulukan 2003). Then, the equation of the membership function is:

$$\mu_M(x) = \begin{cases} 0 & x < l \\ \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{6-5}$$

For two triangular fuzzy numbers $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$, they have the following operation laws (Chang 1996):

$$\text{Additive law: } (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{6-6}$$

$$\text{Multiplicative law: } (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) \approx (l_1 l_2, m_1 m_2, u_1 u_2) \tag{6-7}$$

$$(\eta, \eta, \eta) \otimes (l_1, m_1, u_1) = (\eta l_1, \eta m_1, \eta u_1) \tag{6-8}$$

$$\text{Reciprocal law: } (l_1, m_1, u_1)^{-1} = (1/l_2, 1/m_2, 1/u_2) \tag{6-9}$$

6.3.4 Fuzzy MCDM in MFSD approach

In a MCDM problem, let $A = (A_1, A_2, \dots, A_p)$ to be the vector of alternatives and $C = (C_1, C_2, \dots, C_q)$ to be the vector of criteria, then the decision matrix is:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1q} \\ z_{21} & z_{22} & \cdots & z_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ z_{p1} & z_{p2} & \cdots & z_{pq} \end{bmatrix} \tag{6-10}$$

where $z_{ij} (i = 1,2, \dots, p; j = 1,2, \dots, q)$ is the value of the ith alternative under the jth criterion. The relative importance of criteria C is regarded as weights to decisions:

$$w = [w_1, w_2, \dots, w_q] \tag{6-11}$$

In the general MCDM problems, the weights are derived from the subjective basis of expert judgements or decision makers' opinions in terms of their experience and knowledge. In the MFSD approach in this study, the weights are computed on the basis of data-driven model-based contributions of criteria. The model-based contributions of criteria are firstly converted to triangular fuzzy numbers in terms of fuzzy logic method. Then, for the fuzzy MCDM, the decision matrix is composed by the triangular fuzzy numbers with the equation:

$$\tilde{Z} = \begin{bmatrix} \tilde{z}_{11} & \tilde{z}_{12} & \cdots & \tilde{z}_{1q} \\ \tilde{z}_{21} & \tilde{z}_{22} & \cdots & \tilde{z}_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{p1} & \tilde{z}_{p2} & \cdots & \tilde{z}_{pq} \end{bmatrix} \tag{6-12}$$

where $\tilde{z}_{ij}$ is a triangular fuzzy number.

6.3.5 Fuzzy analytical hierarchy process (FAHP)

In the MFSD approach, the FAHP is utilized both for computing the overall indicator for mapping road maintenance burden, and for the decision making for ranking alternatives. AHP has been widely applied in MCDM and GIS-MCDM (Ho 2008, Zahedi 1986, Esmaelian et al. 2015), and the components of the methodology have been continuously improved in previous studies (Ishizaka and Labib 2011). However, AHP is limited in dealing with the uncertainties and even biases from expert judgements and the preference of decision makers by crisp numbers (Feizizadeh et al. 2014). There is still subjectivity in the pair matrix derived from the comparison of expert judgements, and the uncertainty of subjective judgements may have impacts on the final decisions (Kritikos and Davies 2011). Fuzzy set theory is utilized in MCDM through the membership functions of criteria to replace the crisp numbers (Bingham, Escalona, and Karssenberg 2016). Thus, FAHP is increasingly applied for decision making, especially GIS-MCDM, by integrating AHP and fuzzy logic approaches. FAHP has many advantages and great flexibility in the alternatives assessment and decision making. First, due to the use of fuzzy membership functions of criteria, the uncertainty from the initial judgments is reduced (Jiang and Eastman 2000). In this study, even the subjectivity of expert judgments is eliminated by the data-driven model-based decision-making approach, the contributions of criteria are still varied in different models for their different strengths in relationship calculation. Second, FAHP can reflect the strengths of multiple models that are used for criteria contribution calculation. The approximate information and uncertainty of the different contributions computed by models are all involved in the decision-making. Finally, FAHP is flexible in addressing the decision problems with multi-source data of criteria, which has great benefits for GIS-MCDM.

Once the model-based contributions of criteria are transformed to triangular fuzzy numbers, then the corresponding fuzzy comparison matrix is:

$$(\mathrm{D})_{p\times p}=\begin{bmatrix}(1,1,1) & (l_{12},m_{12},u_{12}) & \cdots & (l_{1q},m_{1q},u_{1q})\\ (l_{21},m_{21},u_{21}) & (1,1,1) & \cdots & (l_{2q},m_{2q},u_{2q})\\ \vdots & \vdots & \ddots & \vdots\\ (l_{q1},m_{q1},u_{q1}) & (l_{q2},m_{q2},u_{q2}) & \cdots & (1,1,1)\end{bmatrix}_{p\times p} \tag{6-13}$$

where $\mathrm{D}_{ij}=(l_{ij},m_{ij},u_{ij})$ is a pair comparison of criteria c_i and $c_j(i,j=1,\dots,q)$, and $\mathrm{D}_{ij}^{-1}=(1/l_{ij},1/m_{ij},1/u_{ij})$ for $i\neq j$. When criteria c_i is relatively more important than criteria c_j, the values of criteria c_i in triangular fuzzy numbers that range in [1, 9] are higher, and the reciprocal values that range in [1, 1/9] are lower that values of criteria c_j. In decision making based on expert judgements, the triangular fuzzy numbers are integers and their reciprocals derived from linguistic variables (Saaty 2008, Vahidnia, Alesheikh, and Alimohammadi 2009), but they are continuous real numbers within the above ranges in the model-based decision making in this study.

The contributions of criteria $c_i(i=1,\dots,q)$ computed by models $G=[g_1,\dots,g_v]$ under alternatives $A=[a_1,\dots,a_p]$ can be listed as a contribution vector:

$$(B_i')_{1\times(p\times v)}=[\beta_{11}',\dots,\beta_{1v}',\beta_{21}'\dots,\beta_{2v}',\dots,\beta_{p1}',\dots,\beta_{pv}']_{1\times(p\times v)} \tag{6-14}$$

The contribution vector is normalized to [0, 1] and then transformed to [1, 9]. The transformed contribution vector is:

$$(B_i)_{1\times(p\times v)}=[\beta_{11},\dots,\beta_{pv}]_{\ 1\times(p\times v)} \tag{6-15}$$

where $\beta_{jk}(j=1,\dots,p;k=1,\dots,v)$ is an element of the contribution vector B, and its value ranges in [1, 9]. The triangular fuzzy number of the element of contribution vector can be calculated by:

$$T=(l^T,m^T,u^T)=\begin{cases}(1,1,1) & \beta=1\\ (1,\beta,\beta+1) & 1<\beta\leq 2\\ (\beta-1,\beta,\beta+1) & 2<\beta\leq 8\\ (\beta-1,\beta,\beta) & 8<\beta\leq 9\end{cases} \tag{6-16}$$

where $T=(1,1,1)$ means that variables are of equal importance. With the increase of β from 1 to 9, the importance gradually varies from very low to very high. The corresponding reciprocal triangular fuzzy number is $T^{-1}=(1/l^T,1/m^T,1/u^T)$.

Further, the fuzzy extended operation for the ith criteria is computed by:

$$S_i = \sum_{i=1}^{q} D_{ij} \otimes \left[\sum_{j=1}^{q} \sum_{i=1}^{q} D_{ij}\right]^{-1} \tag{6-17}$$

In terms of the operation laws of equation (6-6) - (6-9), the fuzzy triangular number S_i can be calculated as:

$$S_i = \left(\frac{\sum_{i=1}^{q} l_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} u_{ij}}, \frac{\sum_{i=1}^{q} m_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} m_{ij}}, \frac{\sum_{i=1}^{q} u_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} l_{ij}} \right) \tag{6-18}$$

The fuzzy triangular numbers calculated by this equation are critical and used twice in the MFSD approach in this study. First, they are the relative weights of criteria under different alternatives for computing the model-based relative importance of variables. Second, they are relative weights of alternatives under given criteria for decision making.

In FAHP, criteria relative weights and weights of alternatives under each criterion are computed by pairwise comparisons of the degree of possibility of membership functions. The degree of possibility for $M_1 \geq M_2$ is calculated with the equation:

$$V(M_1 \geq M_2) = \begin{cases} 1 & m_1 \geq m_2 \\ hgt(M_1 \cap M_2) = \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)} & m_1 < m_2 \end{cases} \tag{6-19}$$

where $hgt(M_1 \cap M_2)$ is the highest interaction between two membership functions (Chang 1996). To compare two membership functions, both $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ should be calculated. Then, the degree of possibility for a convex fuzzy number that is larger than k convex fuzzy numbers $M_i (i = 1,2, \dots, k)$ is:

$$V(M \geq M_1, M_2, \dots, M_k) = \min\big(V(M \geq M_i)\big) \tag{6-20}$$

Thus, the weight of an element $a_i (i = 1,2, \dots, p)$ can be calculated as:

$$w'^{A}(a_i) = \min(S_i \geq S_k) \, ; k = 1,2, \dots, p; k \neq i \tag{6-21}$$

and the weight vector of alternatives is:

$$w'^{\mathrm{A}} = [w'(a_1), w'(a_2), \dots, w'\big(a_p\big)]^T \tag{6-22}$$

Through the normalization process, the weight vector can be normalized as:

$$w^A = [w(a_1), w(a_2), \dots, w(a_p)]^T \tag{6-23}$$

where w^A is a non-fuzzy number.

6.3.6 Fuzzy technique for order preference by similarity of an ideal solution (FTOPSIS)

In the MFSD-based decision-making process, alternatives are ranked through comparison studies using both FAHP and FTOPSIS. FTOPSIS is the integration of fuzzy logic methods with TOPSIS approach, which provides the coefficients of alternatives based on the relative closeness to the ideal solution. TOPSIS determines the optimal alternative with "the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution" (Opricovic and Tzeng 2004, Hwang and Yoon 1981). The distance between $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ is calculated using the vertex method with the equation:

$$d(M_1, M_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \tag{6-24}$$

In MFSD method, the weights of criteria in FTOPSIS stage are also derived from the model-based contributions of criteria, and the computation process is identical with that for FAHP with equations (5-14) - (5-16). Different from FAHP that the aggregated alternative fuzzy ranks and criteria fuzzy weights are computed using pair-wise comparison of triangular fuzzy numbers, FTOPSIS computes the values separately for the respective models. The alternative fuzzy rank $A_i (i = 1, \dots, p)$ under criterion $C_j (j = 1, \dots, q)$ computed with model $G_k (k = 1, \dots, v)$ is $L_{ij}^k = (l_{ij}^k, m_{ij}^k, u_{ij}^k)$, and the weight of criterion C_j is $w_j^k = (w_{j1}^k, w_{j2}^k, w_{j3}^k)$. Then, the aggregated fuzzy rating $L_{ij} = (l_{ij}, m_{ij}, u_{ij})$ of ith alternative under jth criterion is calculated by:

$$l_{ij} = \min_k (l_{ij}^k), m_{ij} = \frac{1}{v} \sum_{k=1}^{v} m_{ij}^k, u_{ij} = \max_k (u_{ij}^k) \tag{6-25}$$

The aggregated fuzzy weight $w_j^C = (w_{j1}^C, w_{j2}^C, w_{j3}^C)$ for the criterion C_j is computed by:

$$w_{j1}^C = \min_k (w_{j1}^k), w_{j2}^C = \frac{1}{v} \sum_{k=1}^{v} w_{j2}^k, w_{j3}^C = \max_k (w_{j3}^k) \tag{6-26}$$

Through a linear scale transformation, the fuzzy decision matrix is normalized by:

$$(\mathrm{R})_{p\times q} = (r_{ij})_{p\times q}; i = 1,\dots,p; j = 1,\dots,q \quad (6\text{-}27)$$

where

$$\text{for the benefit criteria:}\begin{cases} r_{ij} = (\frac{l_{ij}}{u_j^*},\frac{m_{ij}}{u_j^*},\frac{u_{ij}}{u_j^*}) \\ u_j^* = \max_i(u_{ij}) \end{cases} \quad (6\text{-}28)$$

or

$$\text{for the cost criteria:}\begin{cases} r_{ij} = (\frac{l_j^-}{u_{ij}},\frac{l_j^-}{m_{ij}},\frac{l_j^-}{l_{ij}}) \\ l_j^- = \min_i(l_{ij}) \end{cases} \quad (6\text{-}29)$$

The fuzzy decision matrix is weighted and normalized by:

$$(\mathrm{H})_{p\times q} = [(l_{ij}^H, m_{ij}^H, u_{ij}^H)]_{p\times q} = [h_{ij}]_{p\times q} = r_{ij}\times w_j \quad (6\text{-}30)$$

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) of the alternatives are calculated by:

$$\text{FPIS: } A^* = (h_1^*, h_2^*, \dots, h_q^*), \text{ where } h_j^* = \max_i(u_{ij}^H) \quad (6\text{-}31)$$

$$\text{FNIS: } A^- = (h_1^-, h_2^-, \dots, h_q^-), \text{ where } h_j^- = \min_i(l_{ij}^H) \quad (6\text{-}32)$$

The distance between each weighted alternative and the FPIS or FNIS can be calculated by:

$$\text{Distance to FPIS: } d_i^* = \sum_{j=1}^q d^H(h_{ij}, h_j^*) \quad (6\text{-}33)$$

$$\text{Distance to FNIS: } d_i^- = \sum_{j=1}^q d^H(h_{ij}, h_j^-) \quad (6\text{-}34)$$

where $d^H(M_1, M_2)$ indicates the distance between M_1 and M_2.

Finally, FTOPSIS utilizes a closeness coefficient θ_i to indicate the distances from alternatives to the FPIS A^* and FNIS A^-, simultaneously. The equation for calculating closeness coefficient is:

$$\theta_i = \frac{d_i^-}{d_i^- + d_i^*} \quad (6\text{-}35)$$

The best alternative is determined with the highest closeness coefficient. FTOPSIS stage is run by R *FuzzyMCDM* package, which also can perform fuzzy VIKOR, Fuzzy

MMOORA and Fuzzy WASPAS approaches for fuzzy MCDM (Baležentis and Baležentis 2014, Martin 2016).

6.3.7 MFSD-based indicator for mapping road maintenance burden

To map the road maintenance burden, an overall indicator is computed with the assumption that the road performance is associated with the road characteristics, traffic vehicles and climate conditions, and it can be monitored by a series of road performance indicators. In this research, criteria have two hierarchies: the first-level criteria are road characteristics, traffic vehicle conditions and climate, and the sub-criteria include 21 variables within the three first-level criteria. Thus, the indicator is computed by the two hierarchies respectively. The computation process of the MFSD-based indicator is illustrated in Figure 5-6. The overall indicator equals the sum of the weighted criteria, and the criteria are derived from their respective sub-criteria variables and weights. The MFSD-based indicator computation process (purple rectangle in Figure 6-6) includes two steps: quantifying model-based contributions of criteria, and estimating weights of both sub-criteria and criteria using FAHP. First, contributions of a sub-criteria are calculated with multiple models, including 11 models within three categories, and under four alternative indicators. Through the fuzzy logic transformation presented by equations (6-14) - (6-16) and fuzzy extended operations, the fuzzy numbers of sub-criteria are derived. Then, FAHP is applied to calculate weights of sub-criteria variables. Finally, the criteria values are computed by multiplying sub-criteria variables with the weights. The MFSD-based indicator computation process (purple rectangle) is performed repeatedly for each criterion and the overall indicator.

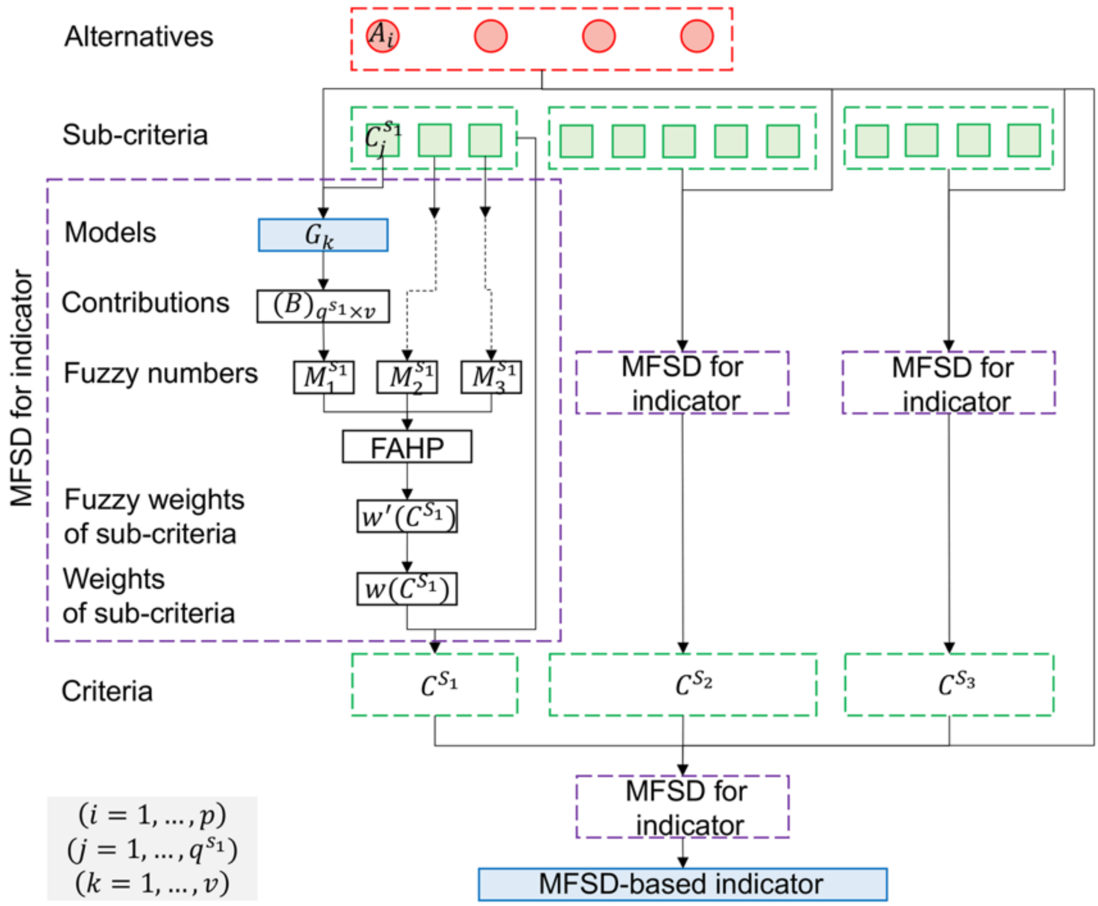

Figure 6-6. Calculation process of model-based fuzzy spatial multi-criteria decision-making (MFSD) based indicator of road maintenance burden

6.3.8 MFSD-based decision making for ranking alternatives and sensitivity analysis

To answer the question that which indicator can more accurately describe the burden of road maintenance, five indicators, including deflection, curvature, roughness, rutting and MFSD-based indicator, are compared using the MFSD approach. The hierarchy frame for the decision-making problem is presented in Figure 6-7. In the MFSD approach, the five indicators are alternatives of the decision, the criteria include road characteristics, traffic vehicles and climate conditions, the sub-criteria consist of 21 variables within three criteria categories, and the contribution computation models include 11 models within three model categories: statistical models, machine learning algorithms and spatial analysis models.

To evaluate the robustness and reliability of MFSD approach, sensitivity of fuzzy MCDM methods is analysed and the burden indicators of road maintenance are evaluated by the comparison with real industrial practice. The sensitivity of fuzzy

MCDM methods are mainly sourced from the sub-criteria variables and the models used for computing contributions of criteria. Thus, each of the sub-criteria variables and the contribution computation models are removed respectively to investigate the variations of the final scores and ranks of alternatives due to the removal of sub-criteria and models. To evaluate the burden indicators of road maintenance, five indicators are compared with the estimated real maintenance cost in the study area in 2015.

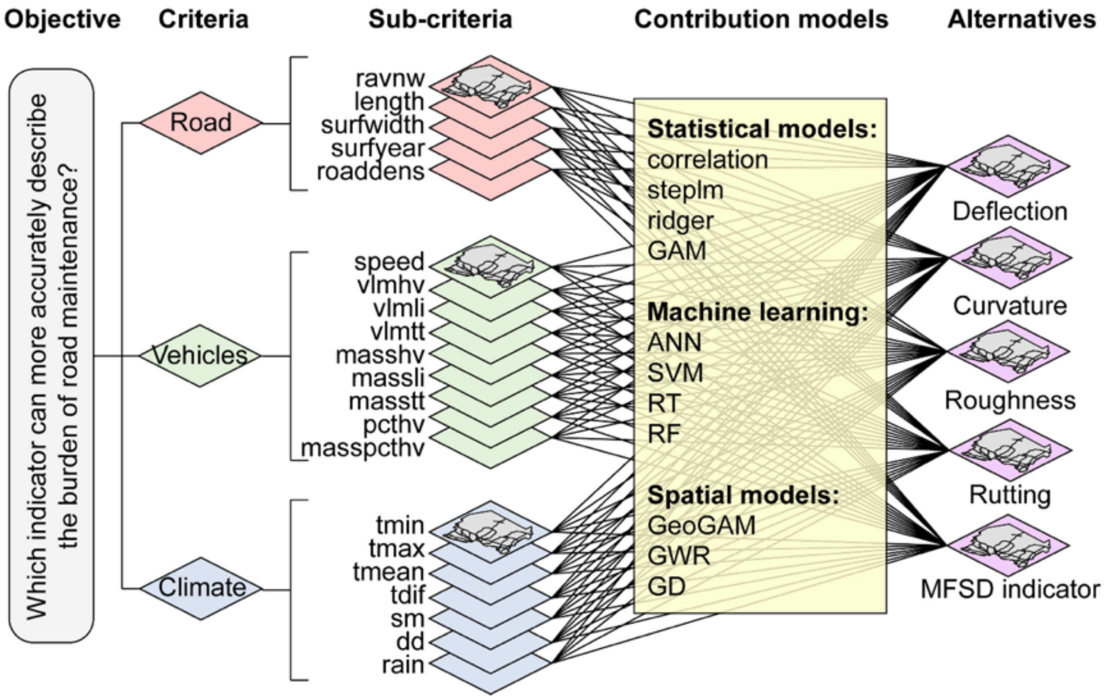

Figure 6-7. Hierarchy frame for model-based fuzzy spatial multi-criteria decision-making (MFSD) method.

6.4 Results and Validation

In this study, an MFSD approach is utilized to capture the burden of road maintenance across the whole road network, and investigate which indicator can more accurately describe the road maintenance burden. The results are presented from four primary parts: (1) model-based contributions to derive fuzzy weights of criteria; (2) an overall indicator for the comprehensive understanding of the burden of road maintenance; (3) fuzzy MCDM for ranking alternatives based on the relative scores; and (4) sensitivity analysis for decision making results and evaluation. Results from four parts are presented in the next four sub-sections respectively.

6.4.1 Model-based contributions and fuzzy weights of criteria

Figure 6-8 shows the summary of model-based contributions of sub-criteria on alternatives. The contribution of a criterion varies with different models and alternatives. According to Figure 6-8, the sub-criteria with the largest mean contributions within three criteria are road density under roughness, total traffic volumes under rutting and soil deep drainage under roughness, respectively. By fuzzy extended operations for the fuzzy numbers of sub-criteria variables under different models and alternatives determined by model-based contributions, the fuzzy membership functions of sub-criteria are derived. Figure 6-9 demonstrates the fuzzy membership functions of sub-criteria of each criterion. The sub-criteria variables with the largest most possible values of fuzzy numbers are surfacing width, traffic speed and soil deep drainage for the three criteria, road, vehicles and climate, respectively. The three sub-criteria variables also have the largest weights within respective criteria (Figure 6-10).

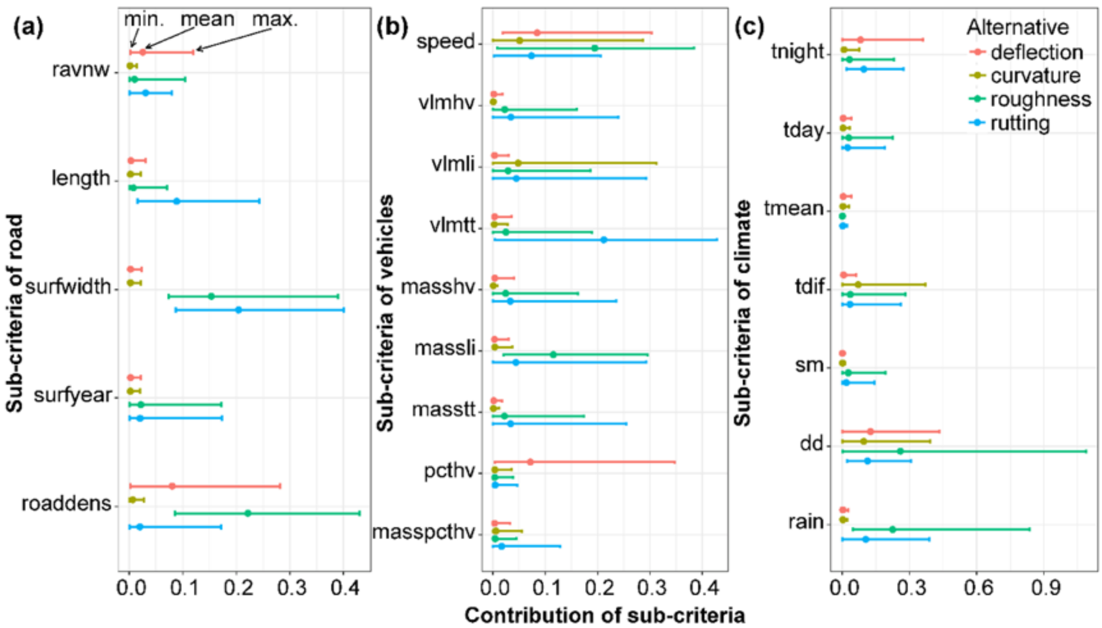

Figure 6-8. Summary of model-based contributions of sub-criteria on alternatives

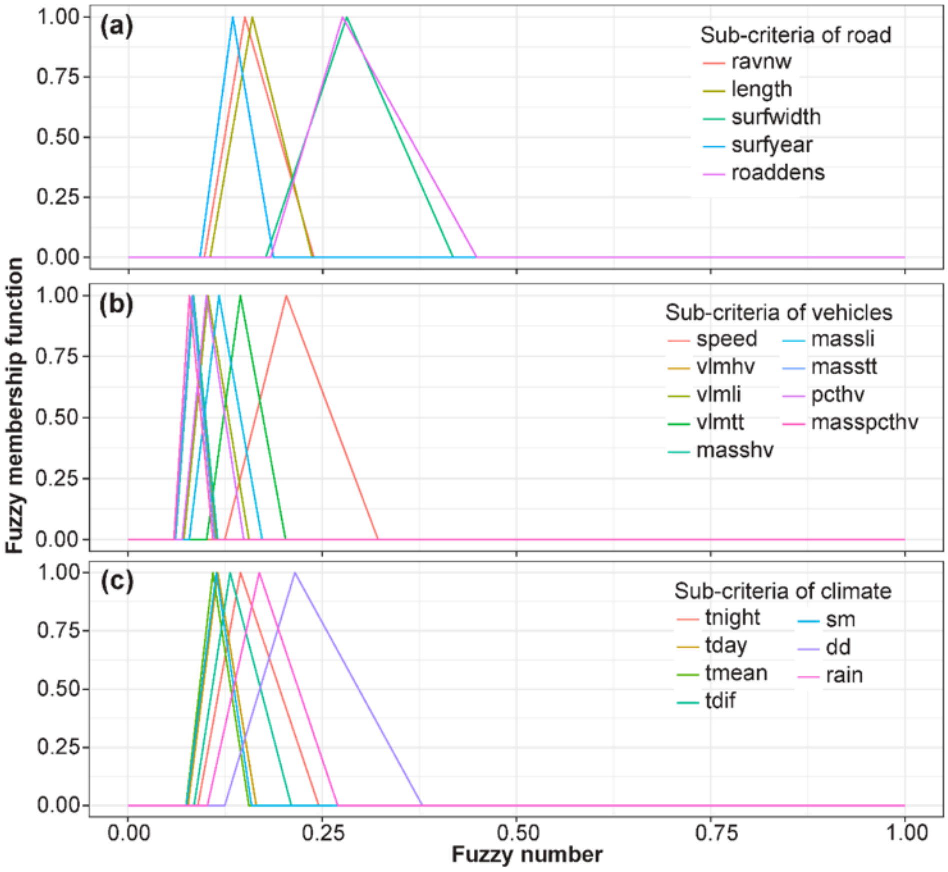

Figure 6-9. Fuzzy membership functions of sub-criteria of each criterion.

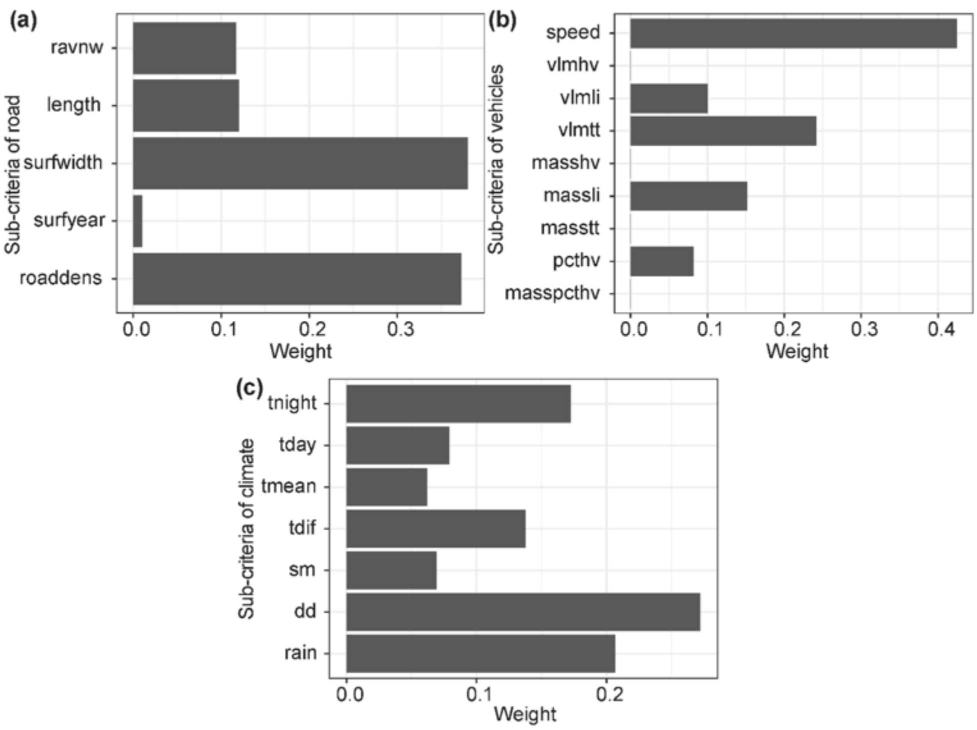

Figure 6-10. Weights of sub-criteria for MFSD-based indicator.

The above process for weighting sub-criteria is repeated for weighting criteria. Figure 6-11 presents the contributions of criteria to the final objective, the fuzzy membership functions of three criteria and the relative weights. Results show that the road performance indicators roughness and rutting can provide more information for the final objective than deflection and curvature. The most possible values of fuzzy numbers and weights of criteria both demonstrate that there is no large difference among the importance of three criteria, where the importance of climate conditions is relatively higher.

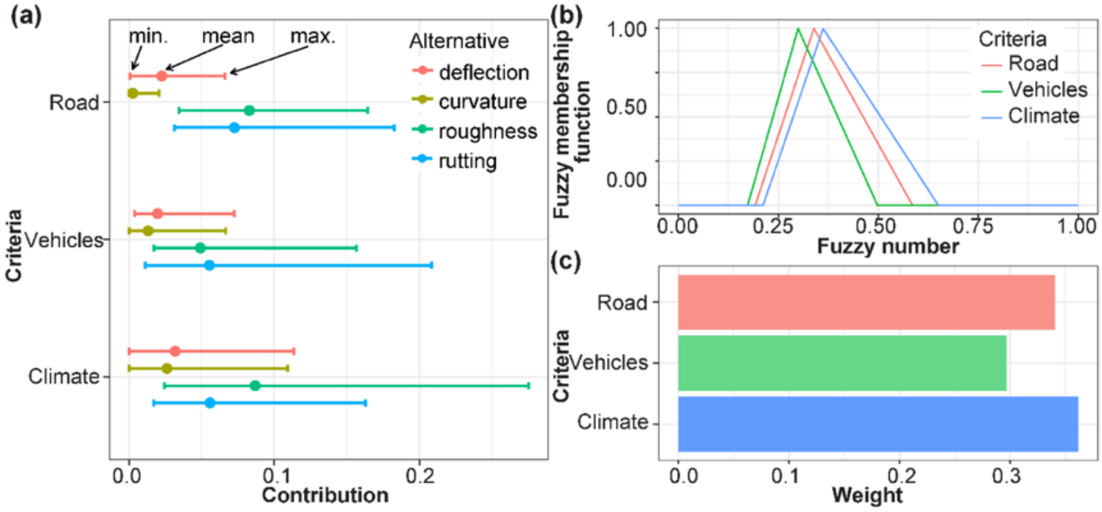

Figure 6-11. Contributions (a), fuzzy membership functions (b) and weights (c) of criteria road, vehicles and climate sectors.

6.4.2 MFSD-based indicator of road maintenance burden

At this stage, MFSD approach is utilized to calculate an overall indicator for describing the road maintenance burden. Figure 6-12 presents results and analysis of the MFSD-based overall indicator of road maintenance burden, including the spatial distributions of MFSD-based indicators, the summary of MFSD-based indicators in local government areas, the map of burden of road maintenance and the value ranges of the maintenance burden. The burden of road maintenance is divided into five levels using natural breaks for the MFSD-based indicator from very high to very low. The roads with very high burden of road maintenance are primarily distributed on the Great Northern Highway, Great Eastern Highway and Albany Highway. The burden of road maintenance across the whole road network is summarized in Table 6-3. About 16.2%

of road segments and 19.2% of the lengths of roads show very high burden of road maintenance.

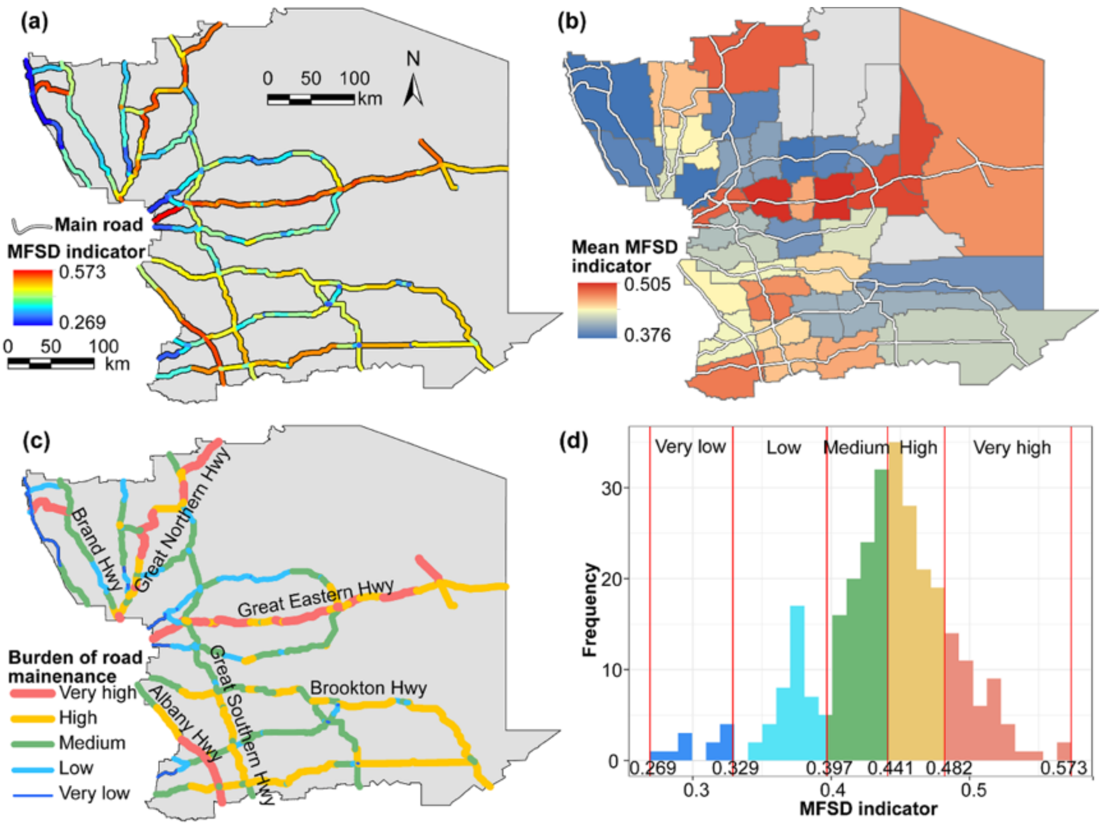

Figure 6-12. Spatial distributions of MFSD-based indicator and the burden of road maintenance. (a) MFSD-based indicator, (b) summary of MFSD-based indicator in local government areas (GLAs), (c) map of burden of road maintenance and (d) value ranges of burdens.

Table 6-3. Summary of burden of road maintenance

Burden of road maintenance	MFSD indicator	Percentage of number	Percentage of length	Percentage of area
Very high	0.482 - 0.573	16.16%	19.23%	22.33%
High	0.441 - 0.482	34.68%	41.48%	40.99%
Medium	0.397 - 0.441	31.99%	31.39%	29.01%
Low	0.329 - 0.397	13.47%	5.49%	5.10%
Very low	0.269 - 0.329	3.70%	2.42%	2.57%

6.4.3 Fuzzy MCDM for ranking alternatives

To answer the question that which indicator can more accurately and reasonably describe the burden of road infrastructure performance, this study utilizes both FAHP and FTOPSIS to rank the alternatives of road performance indicators:

deflection, curvature, roughness, rutting and MFSD-based indicator. Table 6-4 - Table 6-9 list the pairwise comparison fuzzy evaluation matrix under alternatives of each sub-criterion and the pairwise comparison fuzzy evaluation matrix of sub-criteria of each criterion. Table 6-10 lists pairwise comparison fuzzy evaluation matrix of alternatives under each criterion, and Table 6-11 lists pairwise comparison fuzzy evaluation matrix of criteria. Figure 6-13 shows inputs of FMCDM, including fuzzy decision matrix that is the matrix of fuzzy weights of alternatives under criteria, and fuzzy weights of criteria. Figure 6-14 demonstrates the relative scores and ranks of alternatives under different criteria sectors and all criteria. Both FAHP and FTOPSIS methods indicate that the MFSD-based indicator has relatively higher scores than other the four monitored indicators. Among the four monitored indicators, the indicator roughness has highest scores. Thus, based on this result, the MFSD-based indicator is the recommended indicator for describing the burden of road maintenance.

Table 6-4. Pairwise comparison fuzzy evaluation matrix of alternatives under each sub-criteria of road.

Sub-criteria		Pairwise comparison fuzzy evaluation matrix				
ravnw		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1.085,1.378,2.378)	(1.026,1.313,2.262)	(0.715,1.05,1.568)	(0.333,0.433,0.701)
	Curvature	(0.435,0.791,0.956)	(1,1,1)	(0.891,0.947,0.985)	(0.462,0.738,0.971)	(0.241,0.344,0.466)
	Roughness	(0.486,0.883,1.119)	(1.017,1.112,1.294)	(1,1,1)	(0.511,0.839,1.152)	(0.257,0.377,0.524)
	Rutting	(0.805,1.181,1.871)	(1.035,1.471,2.38)	(0.974,1.411,2.275)	(1,1,1)	(0.344,0.514,0.84)
	MFSD indicator	(1.888,2.785,3.695)	(2.896,3.78,4.759)	(2.749,3.596,4.575)	(1.994,2.854,3.778)	(1,1,1)
length		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.01,1.192)	(0.897,0.958,1)	(0.334,0.532,0.801)	(0.233,0.317,0.5)
	Curvature	(0.907,0.991,1)	(1,1,1)	(0.895,0.951,1)	(0.332,0.525,0.801)	(0.23,0.312,0.499)
	Roughness	(1,1.058,1.239)	(1,1.072,1.254)	(1,1,1)	(0.389,0.573,0.9)	(0.244,0.347,0.515)
	Rutting	(1.649,2.353,3.353)	(1.649,2.367,3.367)	(1.602,2.293,3.211)	(1,1,1)	(0.385,0.668,0.869)
	MFSD indicator	(2.845,3.814,4.814)	(2.847,3.833,4.833)	(2.827,3.731,4.731)	(1.53,1.995,2.995)	(1,1,1)
surfwidth		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.002,1.184)	(0.242,0.328,0.526)	(0.213,0.279,0.417)	(0.191,0.241,0.34)
	Curvature	(0.909,0.998,1)	(1,1,1)	(0.242,0.327,0.522)	(0.213,0.279,0.414)	(0.19,0.241,0.338)
	Roughness	(2.438,3.437,4.437)	(2.442,3.442,4.442)	(1,1,1)	(0.586,0.864,1.28)	(0.502,0.765,1.175)
	Rutting	(3.179,4.179,5.179)	(3.184,4.184,5.184)	(0.887,1.247,2.001)	(1,1,1)	(0.587,0.887,1.325)
	MFSD indicator	(3.994,4.903,5.812)	(4,4.909,5.818)	(0.983,1.495,2.347)	(0.852,1.206,1.973)	(1,1,1)
surfyear		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.006,1.188)	(0.828,0.901,0.942)	(0.831,0.909,0.942)	(0.883,0.932,1.053)
	Curvature	(0.908,0.994,1)	(1,1,1)	(0.826,0.896,0.942)	(0.829,0.904,0.942)	(0.882,0.927,1.051)
	Roughness	(1.161,1.296,1.568)	(1.161,1.303,1.575)	(1,1,1)	(0.906,1.015,1.116)	(0.952,1.063,1.253)
	Rutting	(1.162,1.281,1.553)	(1.162,1.288,1.561)	(0.949,0.992,1.193)	(1,1,1)	(1,1.044,1.317)
	MFSD indicator	(1.038,1.186,1.373)	(1.038,1.193,1.379)	(0.894,0.958,1.1)	(0.854,0.964,1)	(1,1,1)
roaddens		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1.55,2.111,2.939)	(0.317,0.481,0.8)	(1.575,2.01,2.934)	(1.626,2.171,3.035)
	Curvature	(0.464,0.665,0.968)	(1,1,1)	(0.214,0.281,0.427)	(0.833,0.975,1.728)	(0.89,0.997,1.786)
	Roughness	(1.494,2.342,3.342)	(3.172,4.172,5.172)	(1,1,1)	(3.043,4.001,4.999)	(3.387,4.295,5.293)
	Rutting	(0.437,0.726,0.924)	(0.783,1.216,1.543)	(0.231,0.318,0.5)	(1,1,1)	(1.055,1.203,1.343)
	MFSD indicator	(0.46,0.723,1.02)	(0.622,1.049,1.285)	(0.223,0.314,0.434)	(0.928,1.011,1.201)	(1,1,1)

Table 6-5. Pairwise comparison fuzzy evaluation matrix of sub-criteria of road.

	ravnw	length	surfwidth	surfyear	roaddens
ravnw	(1,1,1)	(0.829,1.059,1.469)	(0.616,0.794,1.157)	(1.225,1.581,2.17)	(0.973,1.385,1.839)
length	(0.971,1.224,1.615)	(1,1,1)	(0.604,0.77,0.949)	(1.361,1.695,2.17)	(1.062,1.518,1.967)
surfwidth	(1.484,2.005,2.627)	(1.349,1.756,2.397)	(1,1,1)	(2.08,2.637,3.274)	(1.581,2.153,2.615)
surfyear	(0.697,0.889,1.105)	(0.718,0.837,0.994)	(0.518,0.602,0.721)	(1,1,1)	(0.611,0.805,0.943)
roaddens	(1.316,1.695,2.354)	(1.355,1.721,2.403)	(0.836,1.043,1.686)	(1.525,1.865,2.506)	(1,1,1)

Table 6-6. Pairwise comparison fuzzy evaluation matrix of alternatives under each sub-criteria of vehicles.

Sub-criteria		Pairwise comparison fuzzy evaluation matrix				
speed		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1.071,1.365,2.291)	(0.42,0.633,1.033)	(0.702,1.078,1.62)	(0.566,0.849,1.323)
	Curvature	(0.484,0.822,1.059)	(1,1,1)	(0.325,0.51,0.786)	(0.571,0.853,1.296)	(0.431,0.685,1.056)
	Roughness	(1.116,1.798,2.716)	(1.549,2.358,3.358)	(1,1,1)	(1.071,1.775,2.775)	(0.953,1.364,2.277)
	Rutting	(0.741,1.022,1.673)	(0.913,1.324,2.097)	(0.369,0.598,0.945)	(1,1,1)	(0.484,0.792,1.093)
	MFSD indicator	(0.885,1.322,2.106)	(1.158,1.757,2.688)	(0.471,0.752,1.095)	(0.954,1.3,2.211)	(1,1,1)
vlmhv		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.954,1.011,1.105)	(0.825,0.886,0.954)	(0.814,0.861,0.939)	(0.787,0.807,0.852)
	Curvature	(0.951,0.991,1.094)	(1,1,1)	(0.823,0.879,0.954)	(0.812,0.857,0.923)	(0.786,0.805,0.851)
	Roughness	(1.094,1.263,1.536)	(1.094,1.276,1.548)	(1,1,1)	(0.893,0.958,1.103)	(0.817,0.866,0.943)
	Rutting	(1.185,1.397,1.67)	(1.205,1.42,1.693)	(0.952,1.068,1.26)	(1,1,1)	(0.829,0.889,1)
	MFSD indicator	(1.588,1.861,2.134)	(1.631,1.904,2.177)	(1.092,1.31,1.583)	(1,1.189,1.461)	(1,1,1)
vlmli		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.474,0.787,0.932)	(0.821,0.876,0.948)	(0.811,0.857,0.912)	(0.802,0.832,0.908)
	Curvature	(1.275,1.575,2.484)	(1,1,1)	(1.097,1.449,2.244)	(1.086,1.429,2.216)	(1.078,1.404,2.211)
	Roughness	(1.123,1.306,1.579)	(0.689,1.09,1.501)	(1,1,1)	(0.893,0.955,1.1)	(0.842,0.926,1)
	Rutting	(1.276,1.483,1.755)	(0.829,1.262,1.674)	(0.952,1.068,1.258)	(1,1,1)	(0.941,0.983,1.206)
	MFSD indicator	(1.23,1.503,1.776)	(0.789,1.284,1.695)	(1,1.108,1.381)	(0.903,1.055,1.168)	(1,1,1)
vlmtt		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.007,1.189)	(0.831,0.908,0.947)	(0.251,0.367,0.526)	(0.816,0.871,0.933)
	Curvature	(0.907,0.994,1)	(1,1,1)	(0.829,0.903,0.947)	(0.25,0.363,0.516)	(0.814,0.867,0.927)
	Roughness	(1.127,1.256,1.528)	(1.127,1.265,1.538)	(1,1,1)	(0.326,0.432,0.693)	(0.845,0.937,1)
	Rutting	(2.727,3.625,4.625)	(2.741,3.639,4.639)	(2.424,3.265,4.176)	(1,1,1)	(2.375,3.179,4.01)
	MFSD indicator	(1.255,1.446,1.719)	(1.261,1.459,1.732)	(1,1.086,1.358)	(0.386,0.495,0.797)	(1,1,1)
masshv		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.954,1.033,1.125)	(0.827,0.893,0.953)	(0.82,0.877,0.94)	(0.792,0.817,0.88)
	Curvature	(0.947,0.976,1.091)	(1,1,1)	(0.82,0.873,0.953)	(0.814,0.861,0.936)	(0.787,0.808,0.863)
	Roughness	(1.097,1.251,1.523)	(1.097,1.291,1.564)	(1,1,1)	(0.899,0.969,1.097)	(0.82,0.872,0.952)
	Rutting	(1.18,1.35,1.623)	(1.184,1.4,1.673)	(0.953,1.042,1.229)	(1,1,1)	(0.828,0.887,1)
	MFSD indicator	(1.547,1.819,2.091)	(1.647,1.918,2.191)	(1.067,1.28,1.553)	(1,1.2,1.473)	(1,1,1)
massli		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.908,0.994,1)	(0.321,0.499,0.767)	(0.813,0.864,0.912)	(0.231,0.317,0.466)
	Curvature	(1,1.006,1.188)	(1,1,1)	(0.322,0.503,0.767)	(0.814,0.867,0.92)	(0.232,0.32,0.472)
	Roughness	(1.675,2.432,3.432)	(1.675,2.423,3.423)	(1,1,1)	(1.445,2.094,2.966)	(0.475,0.677,1.075)
	Rutting	(1.276,1.472,1.745)	(1.263,1.459,1.731)	(0.451,0.686,1.077)	(1,1,1)	(0.369,0.467,0.74)
	MFSD indicator	(3.243,4.096,5.005)	(3.237,4.084,4.993)	(1.295,1.89,2.72)	(2.949,3.678,4.426)	(1,1,1)
masstt		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.006,1.188)	(0.829,0.899,0.95)	(0.819,0.877,0.937)	(0.799,0.838,0.868)
	Curvature	(0.908,0.995,1)	(1,1,1)	(0.828,0.895,0.95)	(0.817,0.874,0.932)	(0.798,0.837,0.866)
	Roughness	(1.109,1.252,1.524)	(1.109,1.26,1.532)	(1,1,1)	(0.896,0.956,1.093)	(0.825,0.888,0.956)
	Rutting	(1.203,1.39,1.663)	(1.208,1.401,1.674)	(0.954,1.06,1.244)	(1,1,1)	(0.836,0.913,1)
	MFSD indicator	(1.592,1.796,2.069)	(1.61,1.815,2.088)	(1.063,1.254,1.526)	(1,1.147,1.42)	(1,1,1)
pcthv		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1.35,1.867,2.783)	(1.35,1.869,2.787)	(1.348,1.863,2.787)	(1.221,1.631,2.488)
	Curvature	(0.435,0.69,0.968)	(1,1,1)	(0.954,1.001,1.095)	(0.952,0.995,1.094)	(0.856,0.873,0.989)
	Roughness	(0.435,0.689,0.971)	(0.954,0.999,1.093)	(1,1,1)	(0.907,0.994,1)	(0.856,0.87,0.987)
	Rutting	(0.435,0.696,0.978)	(0.954,1.006,1.1)	(1,1.007,1.189)	(1,1,1)	(0.857,0.873,0.995)
	MFSD indicator	(0.63,1.044,1.394)	(1.419,1.642,1.83)	(1.414,1.64,1.824)	(1.399,1.625,1.809)	(1,1,1)
masspcthv		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.95,0.985,1.091)	(0.952,0.995,1.095)	(0.84,0.93,0.965)	(0.23,0.316,0.464)
	Curvature	(0.954,1.018,1.11)	(1,1,1)	(1,1.011,1.193)	(0.888,0.946,1.06)	(0.233,0.321,0.478)
	Roughness	(0.954,1.007,1.101)	(0.906,0.99,1)	(1,1,1)	(0.841,0.935,0.965)	(0.231,0.317,0.471)
	Rutting	(1.057,1.164,1.436)	(1.011,1.146,1.332)	(1.057,1.157,1.43)	(1,1,1)	(0.246,0.342,0.511)
	MFSD indicator	(2.989,3.917,4.917)	(2.94,3.869,4.869)	(2.959,3.894,4.894)	(2.544,3.469,4.469)	(1,1,1)

Table 6-7. Pairwise comparison fuzzy evaluation matrix of sub-criteria of vehicles.

	speed	vlmhv	vlmli	vlmtt	masshv
speed	(1,1,1)	(1.418,2.048,2.951)	(1.329,1.923,2.747)	(1.279,1.839,2.602)	(1.409,2.039,2.923)
vlmhv	(0.434,0.689,1.029)	(1,1,1)	(0.824,0.958,1.083)	(0.817,0.926,1.078)	(0.934,0.996,1.114)
vlmli	(0.494,0.737,1.122)	(1.014,1.13,1.455)	(1,1,1)	(0.905,1.043,1.379)	(1.004,1.124,1.432)
vlmtt	(0.577,0.873,1.321)	(1.23,1.431,1.735)	(1.118,1.376,1.645)	(1,1,1)	(1.23,1.424,1.728)
masshv	(0.445,0.69,1.044)	(0.944,1.006,1.138)	(0.834,0.963,1.104)	(0.819,0.929,1.075)	(1,1,1)
massli	(0.637,0.965,1.434)	(1.466,1.769,2.214)	(1.384,1.712,2.079)	(1.369,1.674,2.137)	(1.457,1.763,2.189)
masstt	(0.435,0.667,1.004)	(0.949,0.99,1.153)	(0.803,0.947,1.045)	(0.81,0.904,1.033)	(0.922,0.984,1.095)
pcthv	(0.455,0.681,1.017)	(0.978,1.129,1.397)	(0.888,1.088,1.386)	(0.877,1.042,1.341)	(0.968,1.122,1.379)
masspcthv	(0.534,0.844,1.257)	(1.215,1.399,1.701)	(1.115,1.357,1.678)	(1.102,1.317,1.637)	(1.187,1.392,1.641)
	massli	masstt	pcthv	masspcthv	
speed	(1.048,1.497,2.247)	(1.423,2.055,2.944)	(1.391,1.992,2.855)	(1.336,1.883,2.689)	
heavypred	(0.704,0.83,1.001)	(0.925,1.02,1.118)	(0.917,1.072,1.281)	(0.838,0.961,1.103)	
lightpred	(0.811,0.945,1.238)	(1.032,1.148,1.507)	(0.993,1.216,1.574)	(0.907,1.096,1.406)	
totalpred	(0.992,1.242,1.53)	(1.244,1.439,1.746)	(1.216,1.501,1.842)	(1.136,1.391,1.689)	
masshv	(0.714,0.834,1.018)	(0.954,1.023,1.172)	(0.923,1.074,1.3)	(0.867,0.965,1.156)	
massli	(1,1,1)	(1.497,1.78,2.266)	(1.45,1.843,2.329)	(1.095,1.391,1.746)	
masstt	(0.677,0.813,0.929)	(1,1,1)	(0.92,1.053,1.261)	(0.85,0.947,1.109)	
pcthv	(0.761,0.952,1.275)	(0.982,1.138,1.397)	(1,1,1)	(0.875,1.044,1.304)	
masspcthv	(0.793,0.922,1.215)	(1.208,1.411,1.686)	(1.162,1.41,1.757)	(1,1,1)	

Table 6-8. Pairwise comparison fuzzy evaluation matrix of alternatives under each sub-criteria of climate.

Sub-criteria		Pairwise comparison fuzzy evaluation matrix				
tnight		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1.108,1.537,2.356)	(0.992,1.464,2.228)	(0.69,0.964,1.496)	(0.543,0.762,1.234)
	Curvature	(0.51,0.759,1.03)	(1,1,1)	(0.839,0.927,0.963)	(0.398,0.686,0.915)	(0.336,0.517,0.863)
	Roughness	(0.618,0.931,1.382)	(1.063,1.172,1.444)	(1,1,1)	(0.468,0.757,1.048)	(0.358,0.567,0.923)
	Rutting	(0.826,1.168,1.776)	(1.161,1.63,2.63)	(1.044,1.454,2.365)	(1,1,1)	(0.52,0.779,1.199)
	MFSD indicator	(1.056,1.597,2.358)	(1.33,2.117,3.117)	(1.152,1.866,2.866)	(0.905,1.341,2.174)	(1,1,1)
tday		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.955,1.003,1.094)	(0.883,0.923,1.056)	(0.842,0.935,0.975)	(0.8,0.83,0.906)
	Curvature	(0.954,0.997,1.091)	(1,1,1)	(0.882,0.921,1.056)	(0.841,0.933,0.975)	(0.8,0.829,0.902)
	Roughness	(1.013,1.177,1.36)	(1.013,1.181,1.364)	(1,1,1)	(0.954,1.022,1.207)	(0.822,0.873,1)
	Rutting	(1.035,1.139,1.412)	(1.035,1.143,1.416)	(0.903,0.981,1.094)	(1,1,1)	(0.818,0.862,0.987)
	MFSD indicator	(1.286,1.556,1.829)	(1.294,1.564,1.836)	(1,1.239,1.512)	(1.016,1.279,1.552)	(1,1,1)
tmean		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.008,1.189)	(1,1.024,1.206)	(0.952,1.015,1.116)	(0.829,0.9,0.954)
	Curvature	(0.907,0.993,1)	(1,1,1)	(0.954,1.016,1.107)	(0.951,1.006,1.109)	(0.827,0.895,0.954)
	Roughness	(0.904,0.98,1)	(0.951,0.987,1.091)	(1,1,1)	(0.951,0.99,1.092)	(0.824,0.886,0.954)
	Rutting	(0.949,0.992,1.103)	(0.95,0.999,1.105)	(0.954,1.012,1.104)	(1,1,1)	(0.872,0.897,1.046)
	MFSD indicator	(1.094,1.241,1.514)	(1.094,1.252,1.524)	(1.094,1.277,1.55)	(1.048,1.267,1.451)	(1,1,1)
tdif		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.515,0.782,1.047)	(0.881,0.922,1.044)	(0.835,0.917,0.957)	(0.278,0.401,0.606)
	Curvature	(1.107,1.485,2.314)	(1,1,1)	(1.034,1.409,2.267)	(0.988,1.403,2.178)	(0.389,0.559,0.929)
	Roughness	(1.053,1.209,1.391)	(0.614,0.995,1.35)	(1,1,1)	(0.952,1,1.191)	(0.301,0.445,0.7)
	Rutting	(1.082,1.2,1.473)	(0.644,0.984,1.429)	(0.907,1.002,1.102)	(1,1,1)	(0.302,0.45,0.699)
	MFSD indicator	(1.896,2.819,3.819)	(1.395,2.17,3.084)	(1.563,2.454,3.454)	(1.563,2.46,3.46)	(1,1,1)
sm		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.908,0.995,1)	(0.832,0.902,0.973)	(0.84,0.926,0.996)	(0.833,0.907,0.971)
	Curvature	(1,1.006,1.187)	(1,1,1)	(0.833,0.906,0.973)	(0.842,0.93,0.996)	(0.834,0.911,0.971)
	Roughness	(1.038,1.191,1.464)	(1.038,1.183,1.456)	(1,1,1)	(1,1.04,1.313)	(0.906,1.004,1.105)
	Rutting	(1.004,1.129,1.401)	(1.004,1.122,1.395)	(0.854,0.965,1)	(1,1,1)	(0.899,0.97,1.098)
	MFSD indicator	(1.042,1.196,1.468)	(1.042,1.187,1.46)	(0.951,0.999,1.194)	(0.953,1.041,1.229)	(1,1,1)
dd		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.954,1.116,1.937)	(0.558,0.844,1.271)	(0.779,1.129,1.833)	(1.188,1.776,2.518)
	Curvature	(0.564,0.904,1.094)	(1,1,1)	(0.474,0.754,1.143)	(0.681,1.001,1.546)	(1.054,1.566,2.32)
	Roughness	(1.207,1.703,2.474)	(1.321,1.879,2.747)	(1,1,1)	(1.474,1.843,2.779)	(1.999,2.555,3.464)
	Rutting	(0.747,1.116,1.639)	(0.857,1.209,1.856)	(0.457,0.774,1.051)	(1,1,1)	(0.987,1.495,2.326)
	MFSD indicator	(0.666,0.922,1.357)	(0.686,0.983,1.435)	(0.346,0.571,0.801)	(0.506,0.753,1.153)	(1,1,1)
rain		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.954,0.999,1.092)	(0.315,0.486,0.759)	(0.428,0.65,0.899)	(0.421,0.621,0.958)
	Curvature	(0.954,1.001,1.093)	(1,1,1)	(0.315,0.487,0.759)	(0.428,0.651,0.899)	(0.421,0.621,0.958)
	Roughness	(1.833,2.618,3.618)	(1.833,2.617,3.617)	(1,1,1)	(0.967,1.422,2.335)	(0.907,1.526,2.129)
	Rutting	(1.245,1.801,2.71)	(1.245,1.799,2.709)	(0.466,0.746,1.083)	(1,1,1)	(0.699,1.028,1.49)
	MFSD indicator	(1.063,1.742,2.651)	(1.063,1.739,2.649)	(0.639,0.819,1.465)	(0.794,1.054,1.677)	(1,1,1)

Table 6-9. Pairwise comparison fuzzy evaluation matrix of sub-criteria of climate.

	tnight	tday	tmean	tdif	sm	dd	rain
tnight	(1,1,1)	(1.041,1.352,1.96)	(1.097,1.463,2.118)	(0.835,1.117,1.66)	(1.07,1.41,2.067)	(0.649,0.993,1.451)	(0.818,1.135,1.592)
tday	(0.642,0.829,1.045)	(1,1,1)	(0.991,1.109,1.293)	(0.701,0.859,0.978)	(0.981,1.062,1.266)	(0.523,0.758,0.993)	(0.734,0.911,1.226)
tmean	(0.599,0.774,0.966)	(0.891,0.946,1.044)	(1,1,1)	(0.695,0.804,0.966)	(0.935,0.984,1.138)	(0.512,0.699,0.935)	(0.651,0.802,1.065)
tdif	(0.768,1.073,1.526)	(1.123,1.368,1.867)	(1.152,1.485,1.959)	(1,1,1)	(1.137,1.428,1.94)	(0.697,1.062,1.504)	(0.875,1.169,1.699)
sm	(0.604,0.791,0.984)	(0.888,0.964,1.041)	(0.941,1.048,1.171)	(0.683,0.819,0.947)	(1,1,1)	(0.491,0.708,0.903)	(0.638,0.822,1.072)
dd	(1.05,1.418,2.115)	(1.297,1.722,2.489)	(1.364,1.846,2.594)	(1.1,1.51,2.22)	(1.33,1.77,2.57)	(1,1,1)	(0.97,1.359,2.102)
rain	(0.947,1.242,1.765)	(1.126,1.541,2.074)	(1.175,1.612,2.188)	(0.947,1.313,1.796)	(1.171,1.573,2.176)	(0.661,1.058,1.504)	(1,1,1)

Table 6-10. Pairwise comparison fuzzy evaluation matrix of alternatives under each criterion.

Criteria	Pairwise comparison fuzzy evaluation matrix					
Road		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.995,1.411,2.321)	(0.348,0.538,0.948)	(0.371,0.595,0.961)	(0.285,0.404,0.677)
	Curvature	(0.473,0.772,1.06)	(1,1,1)	(0.287,0.412,0.694)	(0.309,0.459,0.781)	(0.231,0.304,0.454)
	Roughness	(1.067,1.892,2.892)	(1.688,2.638,3.638)	(1,1,1)	(0.949,1.111,2.039)	(0.471,0.752,1.097)
	Rutting	(1.051,1.724,2.724)	(1.556,2.44,3.44)	(0.516,0.915,1.115)	(1,1,1)	(0.403,0.678,1)
	MFSD indicator	(1.591,2.568,3.568)	(2.537,3.537,4.537)	(0.953,1.36,2.275)	(1,1.491,2.491)	(1,1,1)
Vehicles		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(1,1.123,2.123)	(0.462,0.73,1.061)	(0.459,0.73,1.043)	(0.324,0.499,0.831)
	Curvature	(0.474,0.91,1)	(1,1,1)	(0.395,0.673,0.936)	(0.393,0.675,0.924)	(0.307,0.461,0.795)
	Roughness	(1.003,1.445,2.356)	(1.213,1.684,2.684)	(1,1,1)	(0.805,0.985,1.671)	(0.397,0.666,0.988)
	Rutting	(1.061,1.522,2.432)	(1.319,1.801,2.801)	(0.673,1.028,1.424)	(1,1,1)	(0.401,0.674,1)
	MFSD indicator	(1.485,2.322,3.322)	(1.961,2.768,3.677)	(1.013,1.548,2.548)	(1,1.5,2.5)	(1,1,1)
Climate		Deflection	Curvature	Roughness	Rutting	MFSD indicator
	Deflection	(1,1,1)	(0.906,1.068,1.806)	(0.439,0.696,0.966)	(0.527,0.813,1.124)	(0.359,0.593,0.879)
	Curvature	(0.618,0.944,1.194)	(1,1,1)	(0.381,0.656,0.864)	(0.423,0.759,0.935)	(0.344,0.55,0.877)
	Roughness	(1.413,1.881,2.792)	(1.55,2.017,3.017)	(1,1,1)	(1.031,1.279,2.189)	(0.544,0.937,1.242)
	Rutting	(1.132,1.472,2.296)	(1.225,1.543,2.543)	(0.498,0.847,1.05)	(1,1,1)	(0.412,0.712,1)
	MFSD indicator	(1.603,2.257,3.25)	(1.613,2.349,3.343)	(0.934,1.237,2.166)	(1,1.455,2.455)	(1,1,1)

Table 6-11. Pairwise comparison fuzzy evaluation matrix of criteria.

	Road	Vehicles	Climate
Road	(1,1,1)	(0.794,1.166,1.811)	(0.751,1.059,1.694)
Vehicles	(0.662,0.924,1.458)	(1,1,1)	(0.581,0.915,1.249)
Climate	(0.722,1.063,1.615)	(0.909,1.161,1.955)	(1,1,1)

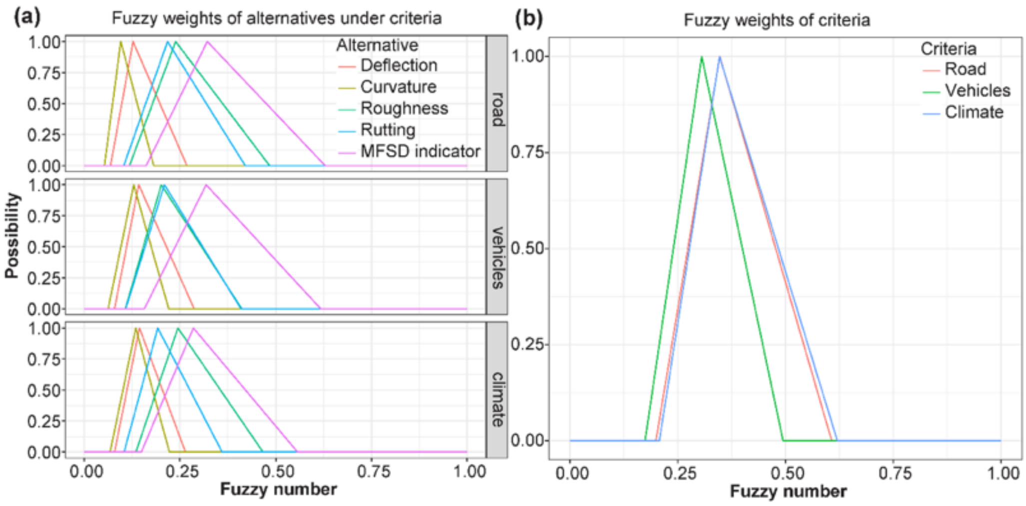

Figure 6-13. The input of fuzzy multi-criteria decision making: (a) fuzzy decision matrix (the matrix of fuzzy weights of alternatives under criteria) and (b) fuzzy weights of criteria.

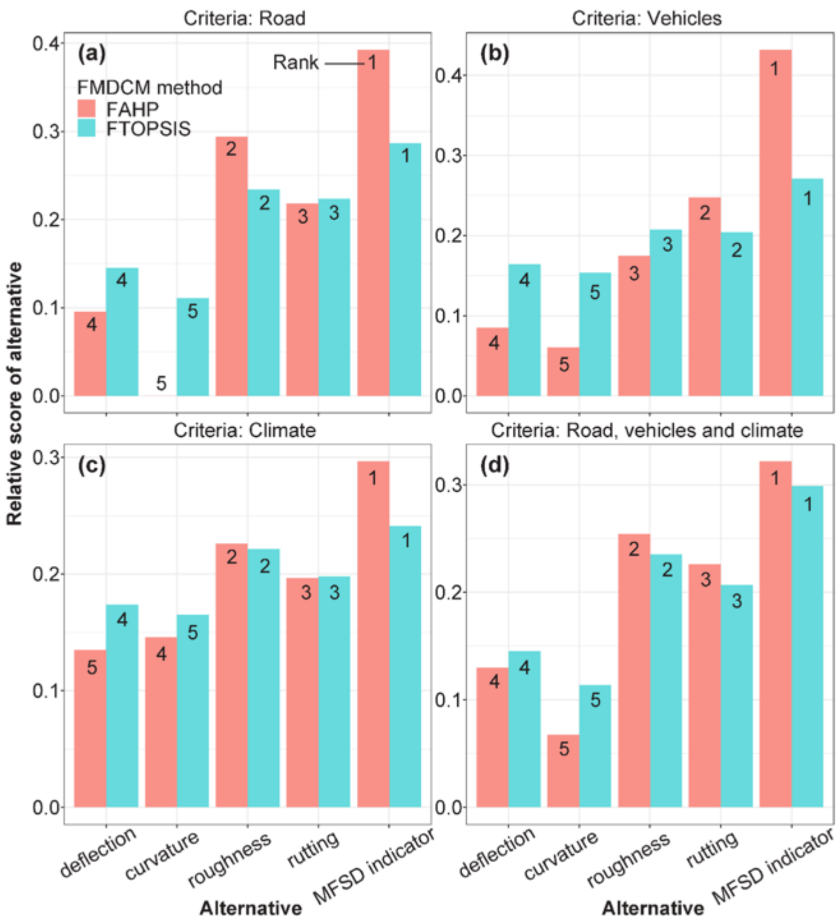

Figure 6-14. Relative scores and ranks of alternatives under different criteria sectors: (a) road, (b) vehicles, (c) climate and (d) all criteria.

6.4.4 Sensitivity analysis and evaluation

6.4.4.1 Impacts of sub-criteria on sensitivity of MFSD results

The impacts of sub-criteria on the sensitivity of decision making using MFSD method are analysed from three aspects. First, the impacts of sub-criteria on the criteria weights in decision making are calculated (Figure 6-15). Both the distributions of criteria weights and percentages of criteria weight changes compared with the full model are not significantly changed due to the removal of sub-criteria. Most of the percentages of weight changes of criteria due to the removal of sub-criteria are lower than 5%. Second, Figure 6-16 shows impacts of sub-criteria on alternative final scores. This result shows that removal of sub-criteria variables does not change the relative scores and ranks of final decision-making results for all three respective criteria sectors and the overall scores of alternatives of both FAHP and FTOPSIS. Finally, Figure 6-17 shows the impacts of each sub-criteria on the overall score and ranking changes of alternatives compared with the full decision-making model. Both FAHP and FTOPSIS indicate that most of the score changes due to removal of sub-criteria variables are lower than 0.02, which is much lower than the scores of alternatives. Nearly all the ranks of alternatives are not changed by removal of sub-criteria variables, except the ranks of roughness and rutting reversed due to removal of soil deep drainage. The above sensitivity analysis indicates that the MFSD method is reliable for decision making and the sub-criteria impacts on final decisions are tiny.

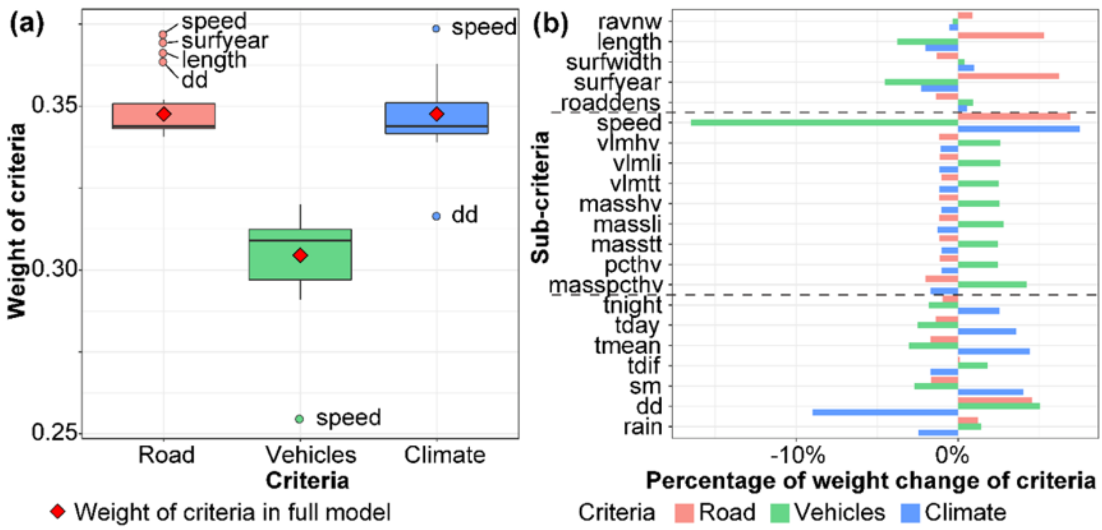

Figure 6-15. Sensitivity analysis of criteria: impacts of sub-criteria on the criteria weights in decision making. (a) Distributions of weights of criteria and (b) percentages of weight changes of criteria compared with full model.

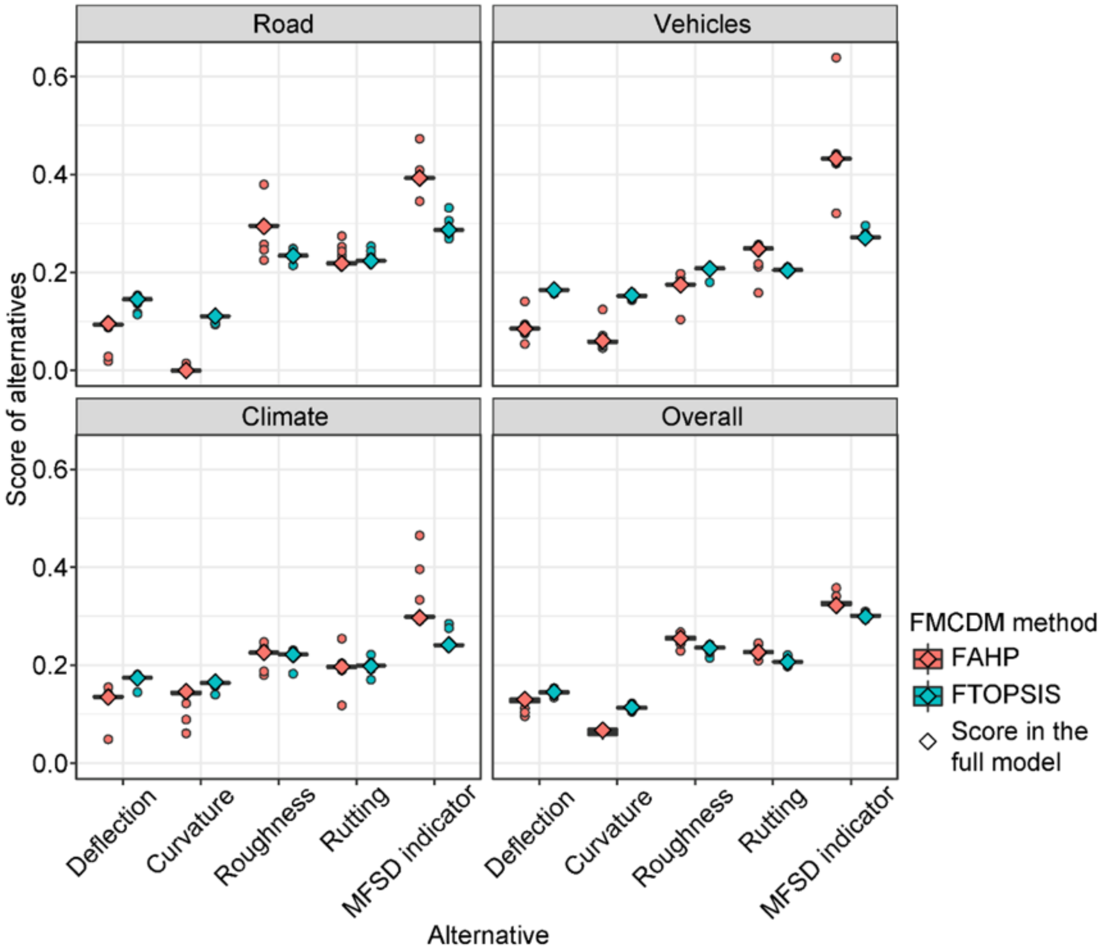

Figure 6-16. Sensitivity analysis of criteria: impacts of sub-criteria on the scores from the sectors of road, vehicles and climate, and the overall scores of alternatives.

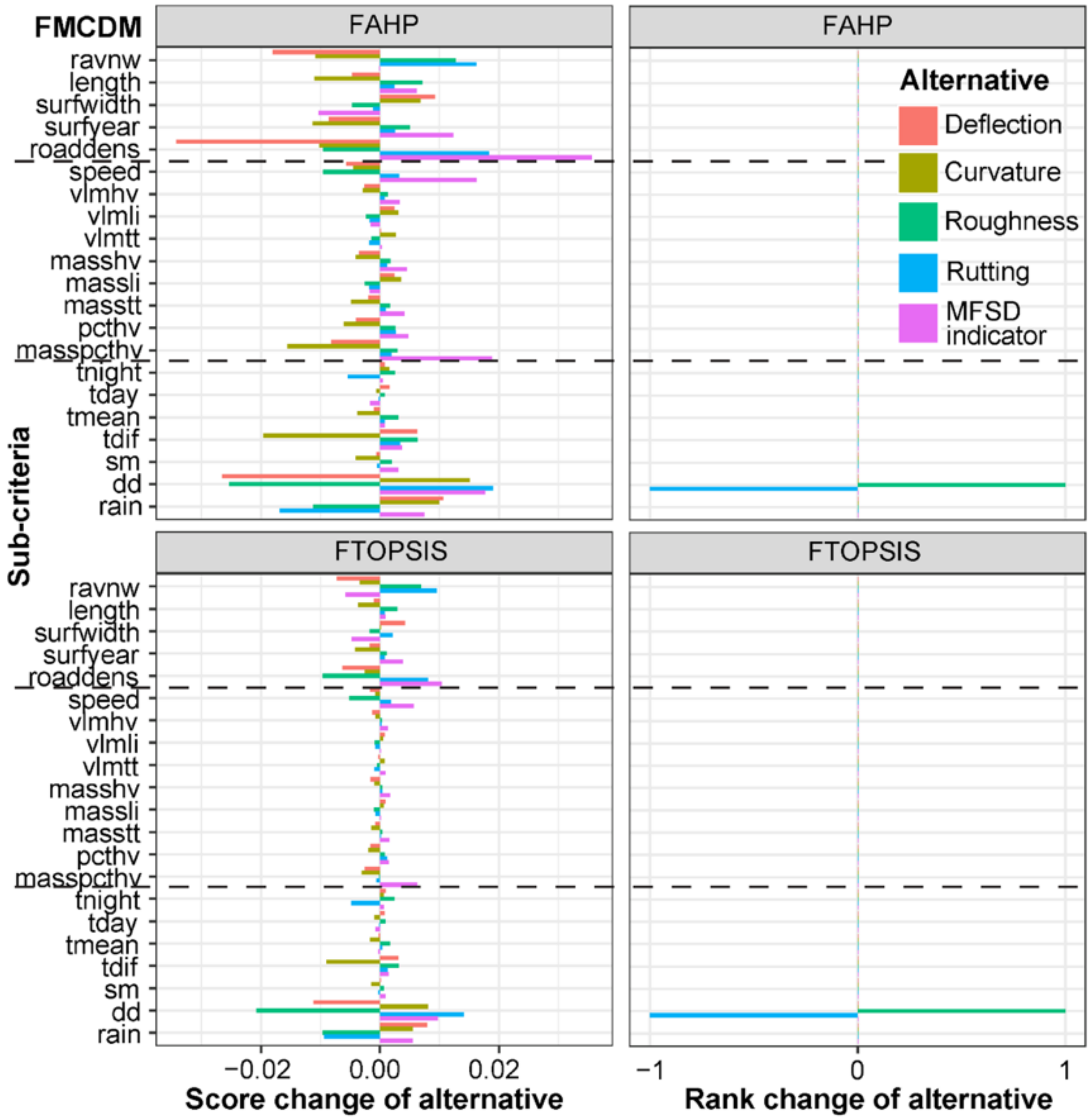

Figure 6-17. Sensitivity analysis of criteria: impacts of sub-criteria on the overall score and rank changes of alternatives compared with the full model.

6.4.4.2 Impacts of contribution computation models on sensitivity of MFSD results

Similar to the sensitivity analysis process of sub-criteria variables, the sensitivity of the impacts of contribution computation models is also analysed through three steps. First, impacts of contribution models on criteria weights and percentages of criteria weight changes compared with the full model are assessed (Figure 6-18). Results show that the changes of criteria weights due to the models are very small. Most of the percentages of weight changes of criteria are lower than 2%, and all of them are lower than 4%. Next, Figure 6-19 presents the impacts of contribution models on the decision scores from the sectors of road, vehicles and climate, and the overall scores of alternatives. FAHP and FTOPSIS both reveal that the relative scores and ranks of alternatives are not significantly varied due to the contribution models. Finally, Figure 6-20 shows the impacts of contribution models on the overall score and rank changes of alternatives compared with the full model. All of the score changes of alternatives are lower than 0.008, which is much lower than the scores of alternatives, and all the ranks of alternatives are not changed. Results demonstrate that final decision making is almost unaffected by the contribution computation models. In addition, FAHP is more capable of differentiating the relative importance of alternatives than FTOPSIS, since FAHP involves pair-wise comparison of the fuzzy membership functions of criteria.

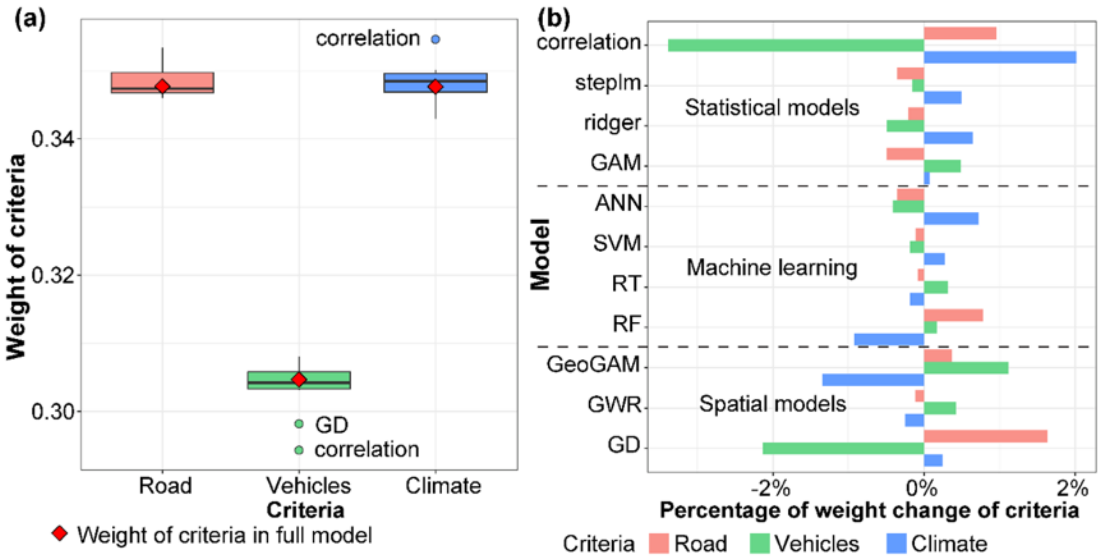

Figure 6-18. Sensitivity analysis of contribution models: (a) impacts of contribution models on the weights of criteria and (b) the percentages of weight changes of criteria compared with the full model.

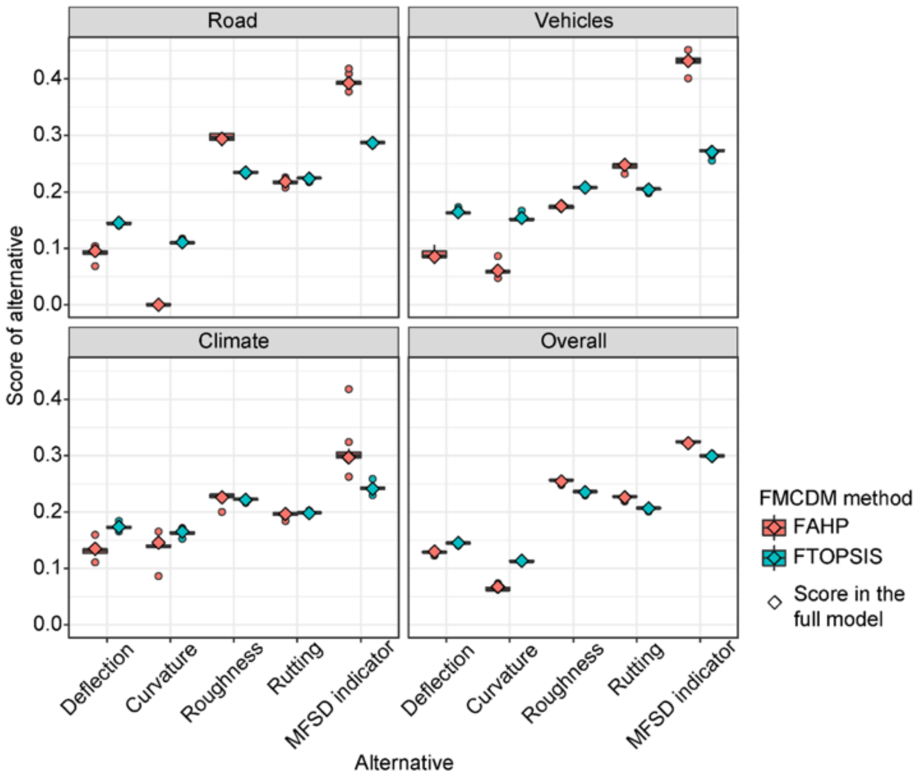

Figure 6-19. Sensitivity analysis of contribution models: impacts of contribution models on the scores from the sectors of road, vehicles and climate, and the overall scores of alternatives.

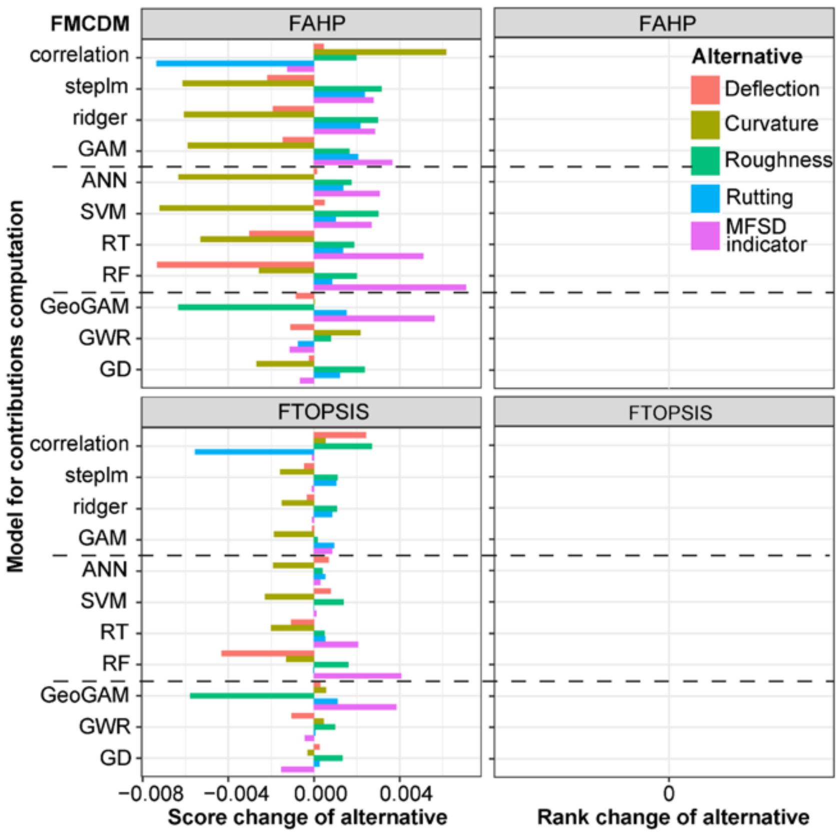

Figure 6-20. Sensitivity analysis of contribution models: impacts of contribution models on the overall score and rank changes of alternatives compared with the full model.

6.4.4.3 Compare indicators with road maintenance cost

To assess the usability of indicators, they are compared with the estimated road maintenance cost in the study area in 2015. The road maintenance cost is estimated by the sum of multiplying the standard cost of different types of road defects with the total areas of defects along the road network. Then, the estimated road maintenance cost is summarized with the spatial unit of road segment. Table 6-12 shows the comparisons between the estimated road maintenance cost and the indicators of road maintenance burden, including deflection, curvature, roughness, rutting and MFSD-based indicator. Due to the bias distribution of real road maintenance cost data, the log-transformed real road maintenance cost is used for correlation analysis. The correlation analysis reveals the correlation coefficient of MFSD-based indicator is much higher than other indicators. Meanwhile, the MFSD-based indicator and roughness are the only two indicators where their significance levels of correlations are lower than 0.01. Therefore, the MFSD-based indicator is the best choice and roughness is the preferred choice among four monitored indicators of road performance.

Table 6-12. Comparisons between the real road maintenance cost and the indicators of road maintenance burden

Indicator of road maintenance burden	Correlation coefficient	Significance
Deflection	0.123	$p < 0.05$
Curvature	0.112	$p = 0.054$
Roughness	0.151	$p < 0.01$
Rutting	0.112	$p = 0.053$
MFSD-based indicator	0.197	$p < 0.01$

6.5 Discussion

This research utilizes a geospatial decision-making method for more accurate description of the road performance and burden of road maintenance. The MFSD method is built through the integration of data-driven model-based contribution computation, fuzzy set theory, geospatial analysis and decision making and multi-criteria decision making. The MFSD approach supports deriving an overall indicator for describing the burden of road maintenance and the decision making for determining a relatively preferred indicator for accurate and flexible road asset management. The MFSD approach has the following advantages in decision making:

- Both criteria and alternatives data are spatial data that not only reflect the values of variables, but also present the spatial relationships;
- Model-based contribution computation for criteria is a data-driven method, which can avoid the uncertainty, potential biases and subjectivity of expert judgements and decision makers' opinions that may have impacts on the final decisions (Kritikos and Davies 2011);
- In the model-based contribution computation process, multiple models from different perspectives, including statistics, machine learning and spatial analysis, are utilized to calculate the contributions of criteria with various aspects and improve the accuracy of decision making;
- Fuzzy set theory is utilized to involve criteria contributions computed by models under alternatives in the overall indicator calculation and decision making;
- FAHP and FTOPSIS are comparatively utilized to make decisions for determining the best indicator for assessing the burden of road maintenance, which can evaluate the advantages and disadvantages of different fuzzy MCDM approaches for more reliable and reasonable decisions.

In addition, for the implementation of the methodology and outcomes of the study, the burden of road maintenance is analysed at the local government area (LGA) level. Figure 6-21 shows the comparison between average MFSD-based indicator and the road maintenance cost in LGAs. The result indicates that the MFSD-based indicator and the road maintenance cost are significantly correlated at the LGA level. The LGAs are divided into six groups in terms of their relative locations along the six primary roads. The LGAs along Brand Highway have the lowest burden of road maintenance. For other LGAs, the burden of road maintenance varies due to their location in the road network.

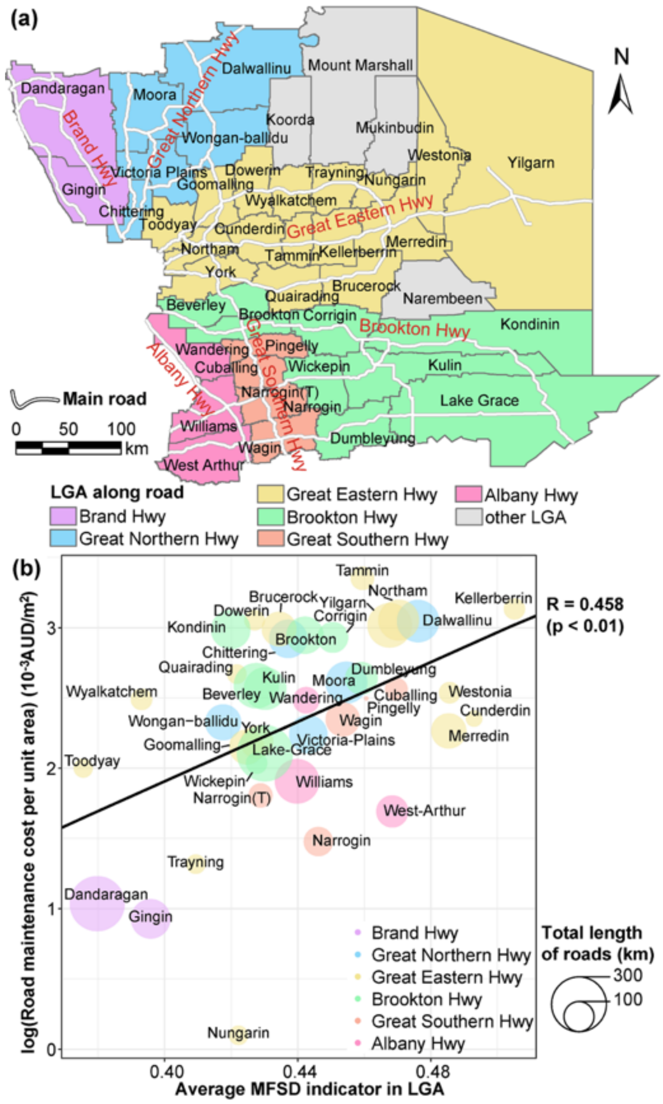

Figure 6-21. Comparison between average MFSD-based indicator and the road maintenance cost in local government areas (LGAs).

6.6 Conclusion

This study proposes an MFSD approach for the geographically local, more accurate and flexible decision making of road maintenance and management. MFSD method can provide more accurate decision-making strategies due to the integration of data-driven model-based contribution computation and fuzzy set theory. It is also a flexible approach where the components and parameters, such as the contribution computation models and FMCDM methods, can be varied based on certain scientific and practical issues. The results in this study can provide informative knowledge and quantitative evidence for the practical decision making of traffic environment assessment, road performance monitoring evaluation and design, road management and maintenance. In addition to traffic and road problems, MFSD method also has wide and great potential in addressing geospatial decision-making issues in other fields, such as environment and public health.

Chapter 7 Conclusions and Recommendations

7.1 Introduction

This thesis systematically studies the impacts of heavy vehicle freight transportation on the traffic and road environment using geospatial analysis methods. To comprehensive investigate the road infrastructure performance and factors of pavement performance for more accurate, geographically local, flexible and reliable decision making, this study develops a series of new geospatial methods and brings new theories and technologies together for road and traffic data analysis.

From the perspective of geospatial analysis, this thesis has significant contributions on the line segment based spatial data analysis. First of all, line segment based spatial data is defined for the traffic and road attributes that are spatially distributed along roads. Segment-based spatial data is totally different from traditional point-based spatial data from the perspectives of spatial morphology, heterogeneity and associations. To address the issues for segment-based spatial data, including spatial prediction, factors exploration and decision making, a series of segment-based spatial analysis methods are proposed in this study. Therefore, this thesis enriches the types of spatial data and provides proper solutions to deal with and to deeply understand the data and the scientific problems.

In this chapter, the thesis is concluded from three aspects. First, research objectives presented in Chapter 1 are revised to summarise the proposed methods, research findings and academic contributions for satisfying objectives in this study. Next, in terms of the methodologies, outcomes and limitations, future research is recommended from integrating multidisciplinary knowledge and techniques for traffic and road environment management and improving data analysis methods. Finally, future industrial practices the can be improved based on this research are recommended.

7.2 Revisiting the research objectives

7.2.1 Road infrastructure performance and factors: Review from a GIS perspective

The first research objective is to critically understand road infrastructure performance and potential factors that have influence on pavement from a geographical information systems (GIS) perspective.

This objective has been satisfied in this research by conducting a thorough and systematic literature review, which provides background and basis of this study. The review includes the following four parts.

(1) To understand impacts of heavy vehicle freight transportation on the road damage and the burden of road maintenance, the association between traffic behaviours and road damage, and methods of evaluating the burden of road maintenance are reviewed. The review indicates that the total masses of vehicles on the road network play a significant role in the cumulative burden of road maintenance. Due to various types and volumes of vehicles, masses of vehicles are distinct on different road segments. Thus, accurate predictions of traffic volumes for different types of vehicles and on various road segments across the road network are required to quantify the burden of road maintenance.

(2) To comprehensively investigate factors associated with the road infrastructure performance, both methods and findings of potential factors that have influence on road damage in previous research are reviewed. In the review, the commonly used multi-source factors of road infrastructure performance are summarised into four categories: vehicles, climate and environmental conditions, road and pavement information, and local socio-economic conditions.

(3) To understand the advantages and potential of decision making in traffic environmental impacts of heavy vehicle freight transportation, the review in this part includes two parts. First, the issue about how to characterise infrastructure performance is addressed. Measures of road infrastructure performance are reviewed and discussed, since they are commonly used to quantify the quality of service to road users. In addition, geospatial decision-making approaches for road infrastructure management are reviewed. The MCDM and its developments are effective approaches for dealing with complex decision-making problems. They can integrate the

performance of decision alternatives across multiple criteria from various sources to derive a compromise solution of road infrastructure management.

(4) To better satisfy users' requirements in practical road and vehicle management, BIM-GIS integration is reviewed and analysed from the aspect of spatio-temporal statistics. The trends and opportunities of implementing BIM-GIS integration are investigated for road construction and management and the broad architecture, engineering and construction industry. BIM-GIS integration can make full use of the strong parts of BIM and GIS. In this thesis, three hypotheses are proposed for the future research and applications of BIM-GIS integration from a spatiotemporal perspective. The further development of the deeper integration of spatio-temporal statistics and 4D/nD BIM can potentially provide more accurate analysis results, and new sense and knowledge for decision making to satisfy the user requirements of AEC industry across the lifecycle.

7.2.2 Heavy vehicle impacts on the burden of road maintenance

The second research objective is to accurately assess impacts of heavy vehicle freight transportation on the burden of road maintenance. The line segment-based spatial prediction models need to be developed and the road maintenance burden caused by different types of vehicles need to be evaluated.

This objective has been satisfied in this research by predicting different types of traffic volumes and estimating vehicle masses at a road segment level across the whole road network. To assess heavy vehicle impacts on the burden of road maintenance, two segment-based spatial prediction models, segment-based ordinary kriging (SOK) and segment-based regression kriging (SRK), are proposed for the spatial prediction of traffic volumes and masses of different types of vehicles. The segment-based spatial prediction models can provide new insights into the spatial characteristics and spatial homogeneity of a road segment during prediction. Results show that they can more accurately predict traffic conditions compared with traditional methods that deal with point-based observations by involving the spatial geometry information of segments. Segment-based spatial prediction methods are useful approaches for the management of heavy and light vehicles, and can inform wise decision making for road maintenance strategies. An R "SK" package is developed for performing the segment-based spatial prediction methods.

The analysis also reveals that impacts of heavy vehicle freight transportation are greatly varied across the road network. In the Wheatbelt region in Western Australia, the impact of heavy vehicles on road maintenance is much larger than that of light vehicles and it varies across space, and the total impacts of heavy vehicles account for more than 82% of the road maintenance burden even though its volume only accounts for 21% of traffic.

7.2.3 Comprehensive impacts of vehicles and climate on road infrastructure performance

The third research objective is to understand comprehensive impacts of multi-source variables on pavement infrastructure performance. The accurate and geographically local impacts of vehicles, climate and environmental conditions, properties of road and socioeconomic conditions on road infrastructure performance need be investigated.

This objective has been satisfied in this research by proposing segment-based spatial stratified heterogeneity analysis methods and applying the segment-based spatial analysis methods in exploring the relationships between pavement performance and factors. Assessing the performance of pavement infrastructure requires sophisticated analysis and is affected by numerous factors and varies greatly across different roads. In addition to the vehicles that are a primary factor of road conditions discussed above, various other variables also have significant influence on the roads, where their impacts vary greatly on different roads. The segment-based spatial stratified heterogeneity analysis can provide both the impacts of single variables and their interactions. An R “GD” package is developed for applying this approach. The approach provides new ideas for spatial analysis for segmented geographical data and objectively reveals the contributions of explanatory variables on road performance.

The segment-based spatial heterogeneity analysis in the Wheatbelt region in Western Australia reveals that all vehicles and heavy vehicles in particular, and climate and environmental variables are two major categories of factors associated with road damage. Vehicle masses and percentage of heavy vehicle mass have greater contributions to pavement condition than traffic volumes, a commonly used indicator of traffic conditions. Meanwhile, the impacts from soil deep drainage, soil type and precipitation are 6.24, 4.76 and 4.48 times of the impacts of mean temperature on pavement damage, but these factors are rarely considered and temperature is a common indicator of climate. The interactions between the vehicles, and climate and environment variables have much more influence than the independent variables, and they can explain more than half of the road damage.

7.2.4 Data and model-driven geospatial multi-criteria decision making

The final research objective is to more comprehensively describe the overall performance of road infrastructure and to select a more accurate performance indicator. Geospatial decision-making approaches are required for transportation authorities for flexible, accurate and geographically regionalised decisions of road and vehicle management, such as road performance assessment and road maintenance.

This objective has been satisfied in this research by proposing a model-driven fuzzy spatial multi-criteria decision making (MFSD) approach for comparing different monitoring indicators and computing an overall indicator. The MFSD method can both generate an indicator and support decision making by integrating data-driven model-based decision making, fuzzy set theory, GIS and multi-criteria decision making (MCDM). Results show that MFSD-based indicators can more accurately describe the spatial distribution of road maintenance burden compared with monitored indicators. MFSD results can provide informative knowledge and quantitative evidence for the decision making of traffic environment assessment, road performance monitoring design and evaluation, and road maintenance and management. MFSD also has wide and great potential in addressing geospatial decision-making issues in other fields.

The data and model-drive decision making reveals that the MFSD-based indicator can better and more accurately reflect road infrastructure performance than the monitored indicators, including deflection, curvature, roughness and rutting in this study. The road infrastructure performance is associated with the criteria of road characteristics, traffic vehicles, and climate and environmental conditions. In addition to the MFSD-based indicator, roughness is the best indicator of road infrastructure performance among the four monitored indicators.

7.3 Recommendations for future research

In terms of the methodologies, outcomes and limitations, future research is recommended from the following three aspects.

First, traffic and road environment assessment and management are multidisciplinary problems. The knowledge, theories, techniques and management from multiple fields should be combined to address a certain problem to satisfy users' requirements. In this study, transportation, road construction, geospatial analysis, decision making and BIM are used in the traffic and road analysis and evaluation. To further study the impacts of vehicles and climate on road infrastructure performance, theories and methods about global climate change, green supply chain and logistics, population accessibility to roads and facilities are recommended to be used and developed.

Second, geospatial analysis theories about segment-based spatial data and methods can be developed. This thesis defines the concept of segment-based spatial data. A series of segment-based spatial methods are proposed to characterize the spatial geometry, heterogeneity and associations. However, there are still theoretical and methodological problems to solve to deal with segment-based spatial data. For instance, spatial weights and spatial autocorrelation are basic concepts for exploring spatial data, but they have not been investigated. Meanwhile, geographical and spatial regressions that are based on spatial weights and spatial autocorrelation need to be addressed.

Finally, more effective and sophisticated spatial and spatiotemporal statistical analysis methods should be integrated in future BIM-GIS integration to significantly improve overall performance and satisfy users requirements in the AEC industry. Geospatial analysis can be applied in more issues for satisfying users requirements in quality, progress and time, cost, contract, health, safety and environment (HSE), and information management, and the coordination of various sectors. Thus, the comprehensive data-driven spatio-temporal modelling of AEC projects can provide more accurate and dynamic solutions for quantitative analysis, management and decision making in future applications.

7.4 Recommendations for industrial practices

Based on this research, future industrial practices can be improved from the following aspects.

First, data and model-based quantitative studies should be involved in predictive road infrastructure maintenance and road asset management. In predictive road infrastructure maintenance, more accurate and reliable potential risks and future scenarios with higher spatial and temporal resolutions are increasingly required in practical construction management. Data and model-based analysis provides quantitative, accurate, reliable and flexible evidence for decision making in practical road infrastructure maintenance and management.

Second, it is necessary to integrate geospatial information, spatial statistical analysis and geographically local assessment in the life cycle of road infrastructure management. Geospatial information brings geographically local data of both road infrastructure itself and the surrounding climate, environment and socio-economic conditions. Spatial statistical analysis provides wider and deeper understandings of the associations between road infrastructure performance and the surrounding local climate, environment and socio-economic conditions. The associations can be varied across the whole road network and in different time frames.

Finally, the concepts can be improved and new technologies can be further integrated in construction management due to the engagement of spatiotemporal statistical analysis in BIM-GIS integration for the AEC industry. BIM-GIS integration with the support of spatiotemporal statistical analysis brings great potential and opportunities for the further application of new data monitoring and collection technologies. The technologies can better satisfy users' requirements in the AEC industry from management methods to coordination mechanisms, including quality management, progress management and time reduction, cost reduction and control, improvement of health, safety and environment (HSE) performance, information management and the coordination of various sectors.

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