Developing sustainable road infrastructure performance indicators using a model-driven fuzzy spatial multi-criteria decision making method

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Abstract

Road infrastructure performance is closely associated with passengers and freight transportation systems and socio-economic development. The performance of road infrastructure is commonly measured by sensor-monitored indicators, and the ability of monitored indicators in revealing actual performance is generally determined by decision makers and road users. However, it is usually unreliable to directly apply monitored indicators in road performance evaluation, due to the limited aspects of individual sensor-monitored indicators, and potential biases and uncertainties of human experience. To address the issues, this study proposes a model-driven fuzzy spatial multi-criteria decision making (MFSD) approach to derive a comprehensive and accurate indicator of sustainable road performance. In this study, the MFSD approach is applied in exploring the road network in the Wheatbelt region in Western Australia, Australia. Spatial variables of road properties, traffic vehicles and climate conditions are used as criteria in the decision making. Four sensor monitored indicators are collected for estimating contributions of criteria. Results show that the MFSD-based indicator can more comprehensively and accurately characterize sustainable road infrastructure performance. In the study area, the MFSD-based indicator can improve 30.46% of the correlation with road maintenance cost compared with roughness, which is the optimal sensor monitored indicator. At the local government areas, the MFSD-based indicator can explain 45.8% of practical road maintenance cost. Sensitivity analysis from multiple aspects indicates that MFSD is a reliable and accurate method in decision making. The proposed method and analysis have broad potentials in the network-level sustainable infrastructure management.

Keywords: Sustainable road infrastructure; model-driven decision making; fuzzy spatial MCDM; spatial analysis; GIS; machine learning

Word Count: 6681

1 Introduction

Road infrastructure is critical for passengers and freight transportation, which is one of the predominant driver of socio-economic development. In general, the theoretical planned life of road infrastructure is about 25 - 40 years (1), but an increasing number of recent studies reveal that the lifespan might be significantly reduced due to accelerated traffic flows and climate change (2-4). Meanwhile, the road lifespan reduction and the elevated road damage risks are varied in different locations. Thus, it is increasingly critical to more accurately monitor and evaluate the geographically local performance of road infrastructure. A practical approach of road performance assessment is to use monitored indicators, which can directly and accurately quantify the quality of service to road users, such as structural and functional conditions (5). 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 (6-8).

Road infrastructure performance is generally used for indicating the sustainability of roads and it can be measured from four perspectives: pavement condition, traffic capacity, safety and population accessibility (6, 7). Pavement condition indicators reveal the structure and functional condition of the road surface (9, 10). The traffic capacity of roads includes congestion of traffic flows, travel time, and the ratio of volume to capacity (11). Safety indicators can examine if accident rates have associations with road design and pavement conditions (12). Population accessibility indicators are used to quantify the ease and resources with which people can access facilities and services through road transport (13). The above indicators provide quantitative evidence for the design, planning, maintenance and optimization of both public facilities and road infrastructure.

This study focuses on the pavement condition indicators, which is a core component of the sustainable road infrastructure system (14). Pavement performance can be evaluated from multiple aspects, such as structural and functional indicators (10). From the perspective of industrial practice, pavement condition indicators are usually classified into three categories: deformation distresses, surface distresses and texture distresses. Commonly used deformation distress indicators include deflection, curvature, roughness and rutting (15-18). Surface distresses usually indicate the cracking, raveling, different types of potholing and edge breaks on the pavement surface (19-21). Pavement surface texture distress can be measured by the flushing and polishing conditions, texture depth and skid resistance (22-26). The pavement condition indicators are widely applied in pavement management, but it is difficult to use individual monitored indicators to reveal every aspect of pavement performance and satisfy user requirements (6). Therefore, integrating information from multiple monitored indicators is required to more comprehensively assess pavement performance (27).

In addition to pavement conditions, the sustainable road infrastructure performance is also affected by traffic flows and surrounding environment (4, 28-30). Accelerated traffic flow is usually the major 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 (31, 32). From the global statistics, the annual average number of vehicles per capita is 1.27 during 1965 to 2000, but it reaches to 2.71 during 2000 to 2015, and 4.25 during 2010 to 2015 (31). On the other hand, the increased burden of road infrastructure also comes from the pronounced variability of climate change. According to a study about road infrastructure vulnerability to climate change in Alaska, United States, climate change related road damage may cause at least 4.2 billion USD cost and an extra 1.3 billion USD by greenhouse gas emissions during this century (4). Studies in Asia and Africa also show the huge cost 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 (33-35). 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 (4, 28).

In this study, a model-driven fuzzy spatial multi-criteria decision making (MFSD) method is proposed for deriving a comprehensive and accurate indicator to describe the sustainable road infrastructure performance. The MFSD method integrates factors exploration models, fuzzy set theory, geographical information systems (GIS) and multi-criteria decision making (MCDM). First, as a model-driven decision making method, the MFSD method can be used to generate accurate road performance indicators by presenting experts' opinions with data and models to reduce the potential biases and uncertainties of linguistic descriptions. Second, the MFSD method can generate a comprehensive indicator that contains information of both sensor-monitored indicators and factors of road performance, where potential factors include characteristics of roads, traffic vehicles and climate and environmental conditions. Finally, the MFSD method can compare different alternative indicators using scores computed by MCDM. In this paper, the MFSD method is used to assess the sustainable road infrastructure performance of the road network in the Wheatbelt region in Western Australia, Australia. The spatial data of four monitored 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, derived from multi-source data are utilized to characterize the sustainable road infrastructure performance.

2 Literature review of methodology

In this section, we review the literature and concepts associated with the methodology to be applied in this research, including the MCDM method, the GIS-based MCDM (GIS-MCDM) method, the fuzzy MCDM method and the data and model driven decision making methods.

The MCDM is a complex 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 (36). Among the MCDM methods, the analytical hierarchy process (AHP) (37, 38) and the technique for order preference by similarity of an ideal solution (TOPSIS) (39) are commonly and widely used methods due to the simplicity and ease of utilization (40). 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 (37). The TOPSIS method defines that the optimal alternative should be closely approximate the expected solution and far from the rejected ones (36).

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 (40, 41). GIS has advantages over spatial and spatiotemporal characteristics analysis, factors exploration, prediction and simulation. 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 elements and components of the objectives (42). 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 (41, 43-46). Fuzzy set theory uses membership functions to describe the preference comparisons of the attributes of interest (47). The fuzzy MCDM approach provides greater flexibility for the evaluation in terms of geospatial data and the GIS-MCDM process (48).

In addition, compared with traditional methods, data and model driven decision making approaches and support systems can deal with the elevated complexity and uncertainty in the decision-making issues, especially the mega decisions, interdisciplinary and cross-domain problems (49-51). Traditional decision making methods are driven by knowledge from experienced decision makers and experts, so the accuracy of decisions highly depends on the human, leading to the biases and uncertainties caused from human factors (52, 53). Compared with traditional decision making methods, data and model driven methods aim to reduce the biases and uncertainties from human factors. The commonly used models of data and model driven decision making include regression models, classification models, prediction models and simulation models (54, 55). However, data and model driven decision approaches are at the initial stage of development and there is still great potential. First, the framework and processes of data and model driven decision making are not 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, such as the binary integer linear models (56, 57) and fuzzy linear regression (58). These models are practical and direct to derive the relationships between criteria and alternatives, but they are limited in addressing sophisticated issues, such as the GIS-MCDM. Finally, most of previous studies use individual 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 their parameters, the results of association functions might be different, even a few 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.

3 Study area and data

3.1 Study area and alternatives

Road freight transportation is one of the primary modes of transport in Australia. The freight moved by road accounts for 52% of the total tonnage moved and 42% of the total ton-kilometers traveled among the road, rail, sea and air networks in Australia (59). The state road network in Western Australia is one of the largest regional road networks in the world and its performance has been continuously improved to meet the requirements of community, industry and other stakeholders (60). The Wheatbelt region plays a critical role in road freight transportation in Western Australia, linking the metropolitan region with primary mining and agricultural production regions (Figure 1).

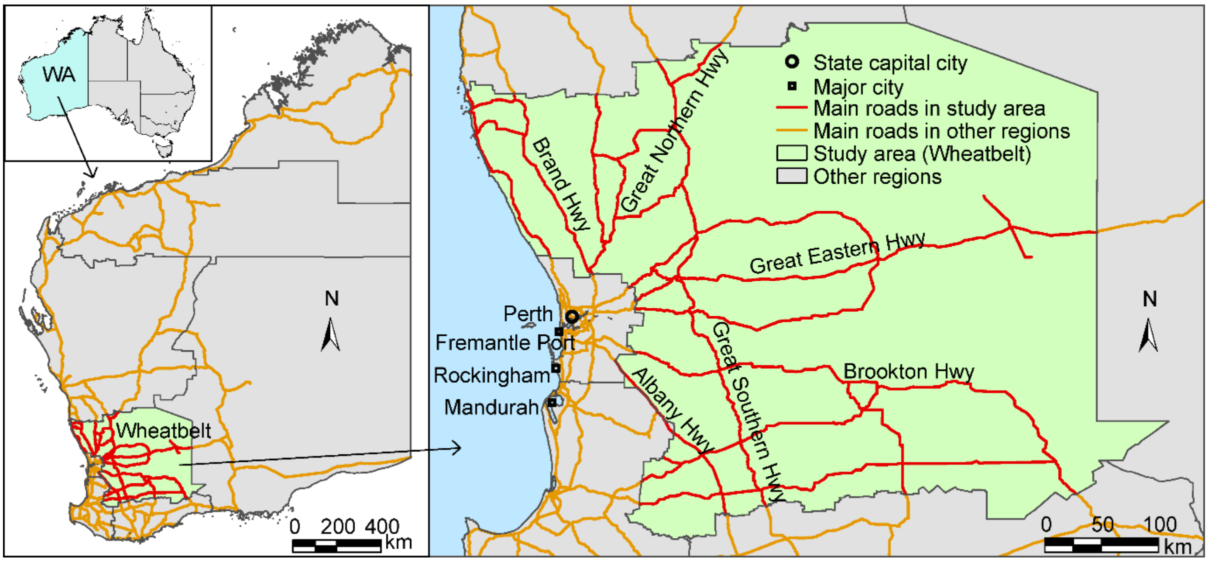

Figure 1. Study area and main road network.

To describe road infrastructure performance, data of four indicators of pavement conditions have been collected by the Main Roads Western Australia, including deflection, curvature, roughness and rutting (Figure 2). In the study, main roads are spatially defined as 297 road segments in the road network, where a road segment is the specific representation of a part of a road with similar construction, geographical and environmental conditions between two junctions or intersections (61-63). Data of four pavement performance indicators are spatially summarized to the road segment based data. **Deflection** measures pavement strength with the maximum depression of pavement surface under a standard load using a Dynatest 8000 series Falling Weight Deflectometer device and is calibrated with Calibration Method WA 2060.5 by Main Roads Western Australia (64, 65). **Curvature** represents asphalt fatigue by 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. **Roughness**, measured by the International Roughness Index, reveals road surface deviations from the intended longitudinal profile. The roughness conditions of pavement can affect vehicle dynamics, vehicle operating costs, driving comfort, and safety and pavement loading. **Rutting** is an indicator of pavement surface and structural conditions and the potential for aquaplaning problems. It is measured as the maximum vertical pavement displacement in the transverse profile through a wheel path (66).

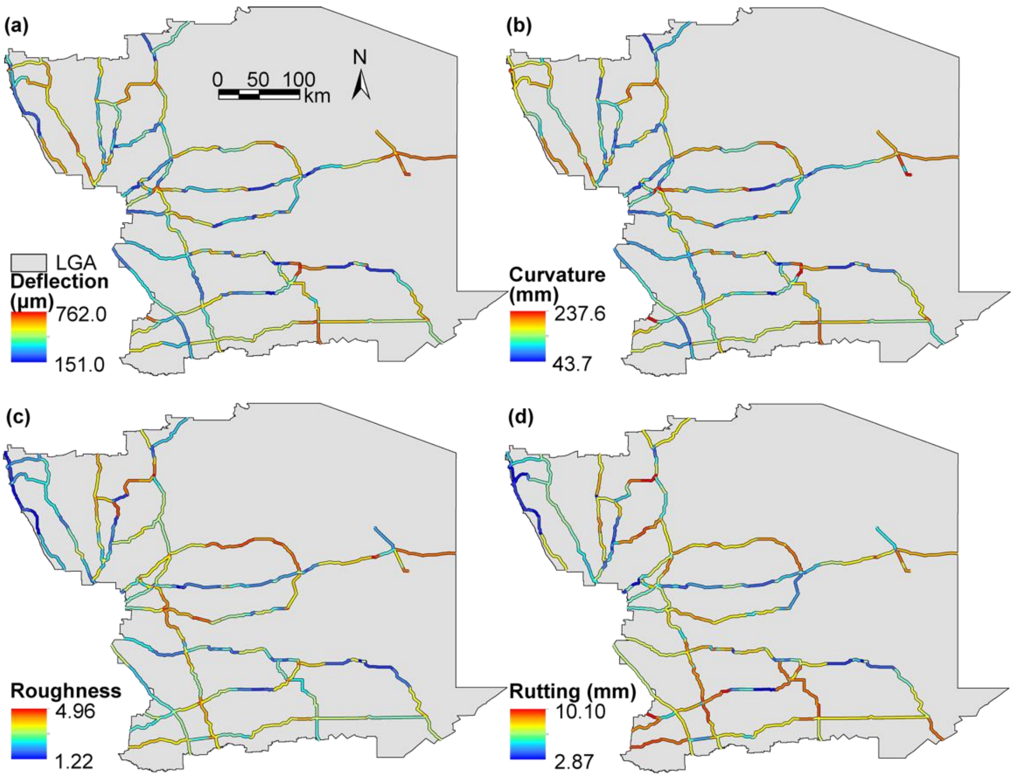

Figure 2. Spatial distributions of sensor monitored road infrastructure performance indicators.

3.2 Explanatory variables of criteria

The explanatory variables of criteria are collected from three categories: road properties, 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 A1-A3, respectively. Variables are pre-processed and summarized to the segment-based data with the consistent spatial unit (road segment) of road performance indicators. The spatial data of explanatory variables of the criteria are listed in Table 1. The brief descriptions and data sources of the three categories of explanatory variables are introduced in the following paragraphs.

Table 1. Summary of spatial data of explanatory variables of criteria

Criteria/ Category	Sub-criteria/ Variable	Code of variable	Min	Max	Mean
Road	Restricted access vehicle networks	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	8.0	1.4
Vehicles	Traffic speed (km/h)	speed	50.8	110.0	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	876.0
	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	25.10	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	9.0
	Deep drainage (mm)	dd	2.3	135.4	25.9
	Annual rainfall (mm)	rain	250.9	681.2	341.0

In this study, road variables are used to describe functions and characteristics of roads and pavement. Restricted access vehicle networks are classified in terms of the maximum permitted mass and size of heavy vehicles (67, 68). According to the requirements, vehicles can only access roads that can support their loads and sizes. Surfacing year is the age of latest pavement surface until 2015. 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 Western Australia and shared by Western Australian Land Information Authority (69).

Vehicles related variables indicate different types of traffic flows. Traffic speed of road segments are summarized based on the legal speed limits (70). Traffic volumes, including heavy and light vehicles, are the annual average daily traffic data monitored by Main Roads Western Australia (60), where traffic volumes on the unobserved road segments are predicted using a segment-based regression kriging method. The segment-based regression kriging can accurately predict traffic conditions by integrating the morphological information of segment-based spatial data and the regression kriging with a segment-based spatial covariance function

(62). As a result, traffic masses on road segments, including the masses of heavy, light and total vehicles, are computed based on the predicted traffic volumes.

Climate criteria variables present near-road local climate and environmental conditions. Climate variables include temperature (71), soil moisture, soil deep drainage and annual rainfall (72). The temperature data are the day-time and night-time temperatures sourced from 8-Day L3 Global Land Surface Temperature (LST) with spatial resolution of 1 km and Emissivity product (MOD11A2) from the Moderate Resolution Imaging Spectroradiometer (MODIS) (73). The soil moisture, deep drainage and annual rainfall data with spatial resolution of 5 km are derived from the soil moisture data products produced by the Bureau of Meteorology, Australia (74). Similar to the road and vehicles criteria variables, the climate data are converted to the road segment-based spatial variables for the spatial consistency.

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

The MFSD method is a decision method integrating MCDM, GIS, fuzzy theory and model-based decision making. As shown in Figure 3, the MFSD method includes following five steps. (1) Criteria are selected from potential explanatory variables. (2) Contributions of criteria and variables on alternatives are computed using three categories of models, including statistical models, machine learning algorithms and spatial analysis models. (3) Fuzzy set theory is used to calculate fuzzy membership functions of criteria to quantify the importance of criteria and criteria weights based on the model-based contributions of criteria. (4) Fuzzy MCDM is used to compute an indicator with the weighted criteria and decision making for ranking alternatives. (5) Sensitivity is analysed for the MFSD-based decision making due to the input parameters. Figure 4 shows the applications of the MFSD method in computing a comprehensive indicator for mapping road maintenance burden and decision making for ranking alternatives of road performance indicators. The five steps of the MFSD method are explained in the sub-sections 4.1 – 4.5, respectively, and the applications of the MFSD method in the decision making for road performance are presented in the sub-section 4.6.

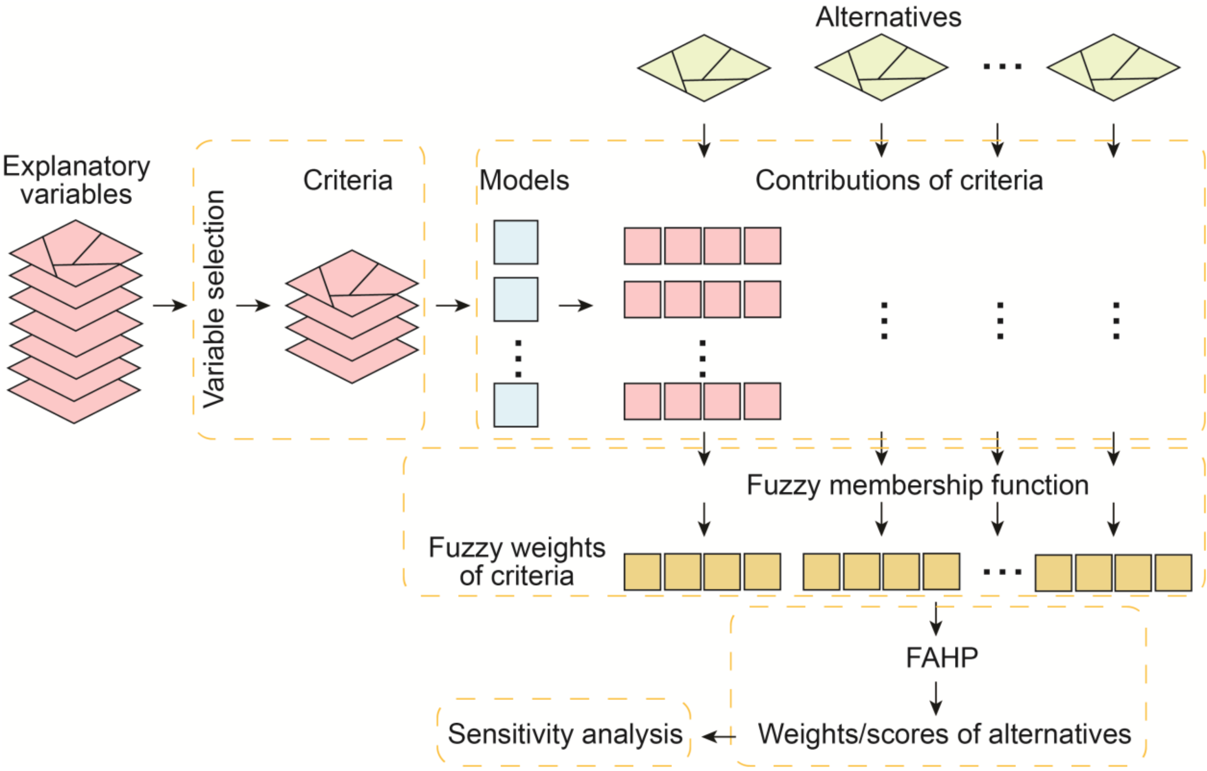

Figure 3. Schematic overview of the model-based fuzzy spatial multi-criteria decision-making (MFSD) method

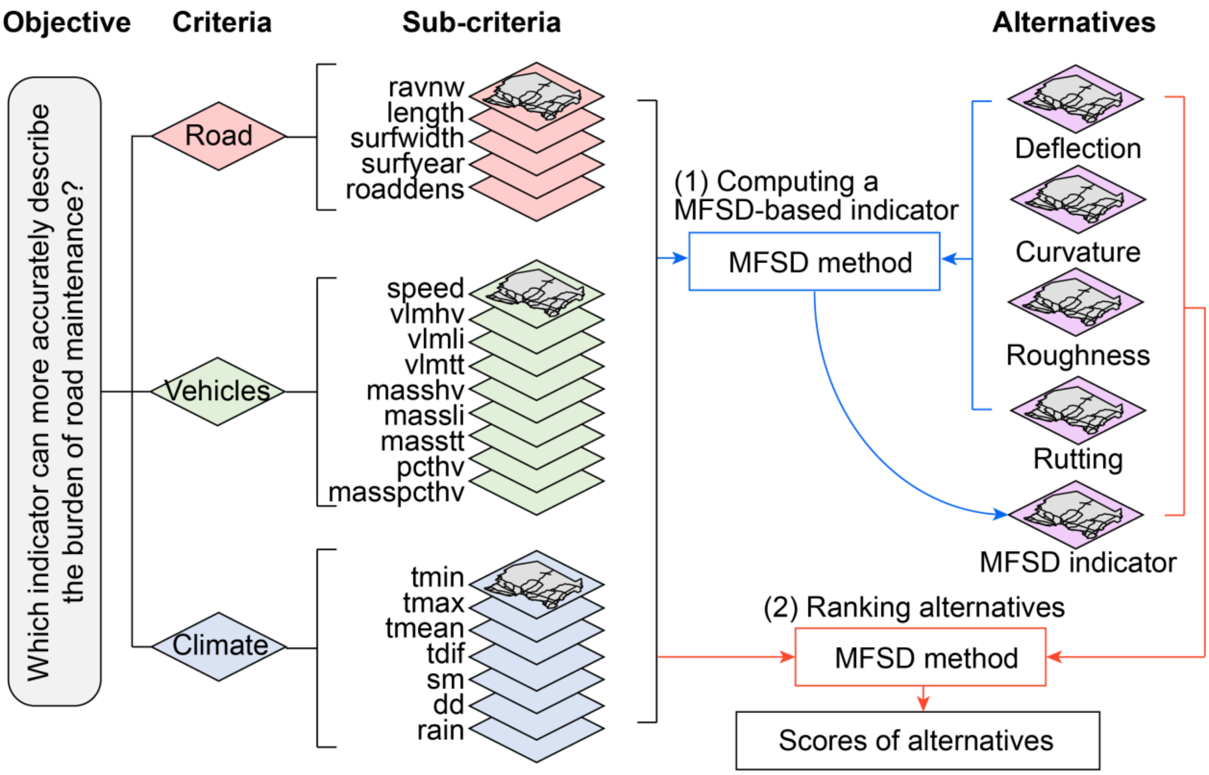

Figure 4. MFSD-based decision making for road infrastructure maintenance, including computing a MFSD-based indicator and ranking alternatives.

4.1 Criteria selection and data pre-processing

Criteria selection consists of two parts. First, data are collected for the potential variables of criteria. The principle of criteria selection is that they should reasonably represent and contribute to the final objective, the overall road infrastructure performance and the burden of road maintenance in this study. Spatial data of 21 sub-criteria of three criteria, road, vehicles and climate, are collected converted to road segment-based data for the consistency of spatial unit. The data are normalized to the range [0, 1] to eliminate unit and scale impacts of different variables using normalization functions (Eq A1 and Eq A2).

Second, variables statistically correlated with alternatives are selected to remove variables without significant correlations. The variable selection in this step varies for different criteria contributions computation models. For the statistical models, machine learning algorithms and spatial regression models (e.g. geographically weighted regression (GWR)), two techniques are recommended: the combination of correlation analysis and multi-collinearity analysis (75, 76), or step-wise linear regression (77). Details of the two techniques are presented in the Supplementary Information. Optionally, if all the selected variables are theoretically associated with the objective, variables with statistically significant correlations with alternatives are not required for a few models, such as ridge regression and geographical detectors, that can internally reduce the impacts of variables that are not significantly correlated with alternatives.

4.2 Model-based contributions of criteria

In the MFSD method, criteria contributions to the objective are computed with multiple models instead of experts or decision makers. In this study, the criteria contributions are repeatedly computed using 11 models in three categories: statistical models, machine learning algorithms and spatial models. Statistical models include correlation analysis, step-wise linear regression, ridge regression and generalized additive model (GAM), machine learning algorithms include artificial neural network (ANN), support vector machine (SVM), regression tree (RT), and random forest (RF), and spatial models include geospatial generalized additive model (GeoGAM), GWR, and geographical detectors (GD). These models are typical models in each category for determining explanatory variables. The models in different categories have their respective strengths and can describe the characteristics of relationships from their respective perspectives. For instance, statistical models capture the relationships from the values of attributes, machine learning algorithms have in-depth understanding of the data, and spatial analysis methods can address the problems related to location-based data and spatial relations. The three categories of models are briefly described in the following three paragraphs, and their mathematical processes are presented in the Supplementary Information.

Correlation analysis examines the contributions of variables to alternatives by correlation coefficients and corresponding significance levels. Step-wise linear regression equals to linear regression if the variables are selected using the step-wise linear regression in the variable selection period. Ridge regression is a robust regression method that can reduce overfitting and multi-collinearity without removing predictor variables (78-80). GAM can describe nonlinear relationships between variables and responses through nonparametric smoothing functions (81).

Machine learning algorithms are different from statistical linear or nonlinear regression in that the forms of functions are pre-specified. 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 reduce overfitting. In ANN, the learning process is performed through a large amount of highly interconnected artificial neurons and weighted links among input and output data (82, 83). In SVM for regression, to determine the best regression function, a hyperplane is constructed to maximize the margin and to minimize the regression error (84). RT constructs a set of decision rules on the explanatory variables (85, 86) and the best split is selected through a thorough search and assessment of splits of all variables. RF constructs a multitude of decision trees during training and outputs the mean prediction of the individual trees for regression (87, 88). RF is robust to noise in data, overfitting problems and small sample sizes, and requires minimal manual parameterization (89).

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 (90, 91). GWR is a critical local method to investigate geospatial non-stationarity of data relationships (92, 93). It enables locally varied regression parameters through location-wise estimation for each spatial variable (94-96). GD is a spatial statistical model for the analysis of spatial data relationships in terms of spatial variance of variables and geographical strata (72, 97-99).

4.3 Fuzzy set theory

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 (100) and uses membership functions to describe the preference of attributes of interest (47). 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 (48). In this study, fuzzy set theory is used to deal with the model-based contributions of criteria to reduce the inherent differences of contributions from various models. During decision making processes, fuzzy set theory can enable pairwise comparison of criteria and alternatives under different criteria. Mathematical processes of fuzzy set theory are presented in the Supplementary Information.

4.4 Fuzzy MCDM in MFSD approach

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

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

where $z_{ij} (i = 1,2, \ldots, p; j = 1,2, \ldots, q)$ is the value of the ith alternative under the jth criterion. The relative importance or called weights of criteria C to the decision can be denoted as:

$$w = [w_1, w_2, \ldots, w_q] \tag{2}$$

In the MFSD approach, 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:

$$\tilde{Z} = \begin{bmatrix} \tilde{z}_{11} & \tilde{z}_{12} & \cdots & \tilde{z}_{1q} \\ \tilde{z}_{21} & \tilde{z}_{22} & \cdots & \tilde{z}_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{p1} & \tilde{z}_{p2} & \cdots & \tilde{z}_{pq} \end{bmatrix} \tag{3}$$

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

Fuzzy AHP (FAHP) is utilized both for computing the comprehensive indicator, and for the decision making for ranking alternatives. First, due to the use of fuzzy membership functions of criteria, the uncertainty from the initial judgments is reduced (101). 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 process (102). Finally, FAHP is flexible in addressing the decision problems and has great benefits for GIS-MCDM.

In this step, the capacity of FAHP in decision making is evaluated by comparison with the Fuzzy TOPSIS (FTOPSIS), where weights of criteria are derived from the identical model-based contributions of criteria. The mathematical processes of FAHP and FTOPSIS are summarized in the Supplementary Information.

4.5 Sensitivity analysis

To evaluate the reliability and robustness of MFSD approach, the sensitivity of fuzzy MCDM methods is analyzed and the burden indicators of road maintenance are evaluated from two aspects. First, 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. In addition, to evaluate the burden indicators of road maintenance, five indicators are compared with the estimated real maintenance cost in the study area.

4.6 MFSD-based decision making for road performance

4.6.1 MFSD-based indicator for mapping road maintenance burden

To map the road maintenance burden, a comprehensive 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 study, the 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 comprehensive 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 includes two steps: quantifying model-based contributions of criteria, and estimating weights of sub-criteria and criteria using FAHP. First, the contributions of a sub-criteria are calculated with multiple models, including 11 models within three categories, and under four alternative indicators, including deflection, curvature, roughness and rutting. Through the fuzzy logic transformation and fuzzy extended operations, the fuzzy numbers of sub-criteria are derived. Then, FAHP is utilized to calculate the weights of sub-criteria variables of a certain criterion. Finally, the criteria values are computed by multiplying sub-criteria variables with the weights. The MFSD-based indicator computation process is performed repeatedly for each criterion and the comprehensive indicator.

4.6.2 MFSD-based decision making for ranking alternatives

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. 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.

5 Results and Validation

In this study, the MFSD approach is developed to capture the sustainable road performance across the whole network, and to investigate capabilities of indicators in describing the road maintenance burden. Results are presented from four primary parts: (1) model-based contributions to derive fuzzy weights of criteria; (2) a comprehensive 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. The results of the four parts are explained in the following four sub-sections, respectively.

5.1 Model-based contributions and fuzzy weights of criteria

Figure A4 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 A4, 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 A5 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 A6).

The above process for weighting sub-criteria is repeated for weighting criteria. Figure 5 presents the contributions of criteria to the final objective, the fuzzy membership functions of three criteria and the relative weights. Figure 5a shows the contributions of criteria road, vehicles and climate sectors on each of the four alternatives, including deflection, curvature, roughness and rutting. The bars indicate the ranges of contributions estimated by the 11 models, and the points show the mean contributions. Results show that the road performance indicators roughness and rutting can provide more information for the final objective than deflection and curvature. Figure 5b shows the fuzzy membership functions, where the lower limit and upper limit of the triangular membership functions indicate the range of fuzzy numbers and the peak values present the fuzzy number with the highest profanities. Figure 5c shows the fuzzy membership functions and wights of the three criteria. 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.

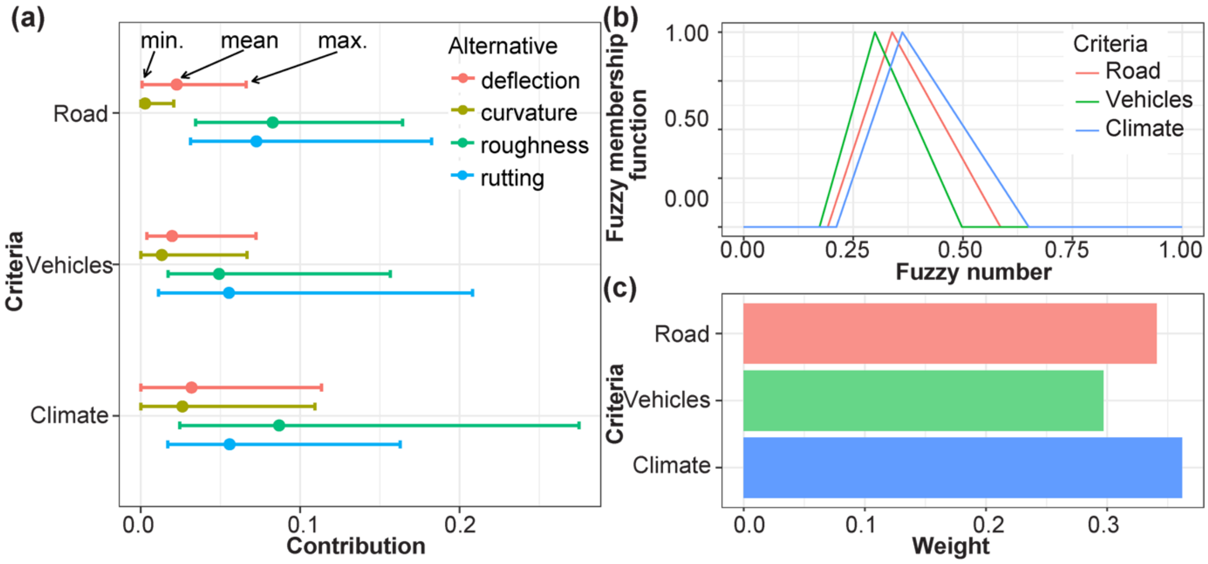

Figure 5. Contributions (a), fuzzy membership functions (b) and weights (c) of criteria road, vehicles and climate sectors.

5.2 MFSD-based indicator of road maintenance burden

At this stage, MFSD approach is utilized to calculate a comprehensive indicator for describing the road maintenance burden. Figure 6 demonstrates the results and analysis of the MFSD-based comprehensive 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: very high, high, medium, low and 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 2. About 16.2% of road segments and 19.2% of the lengths of roads show very high burden of road maintenance.

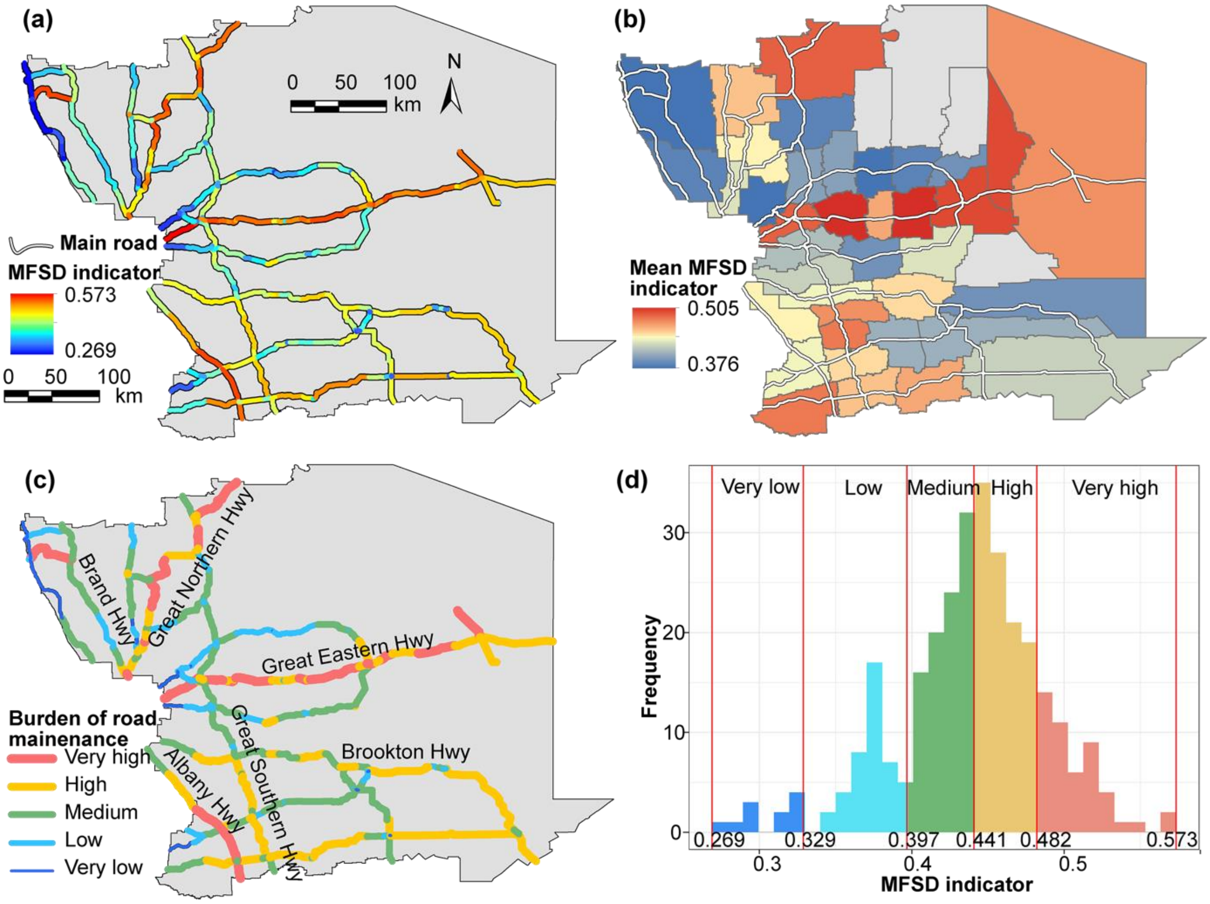

Figure 6. Spatial distributions of MFSD-based indicator (a), local government area-based summary (b), burden of road maintenance (c) and burden ranges (d).

Table 2. 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%

5.3 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. 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 are listed in Tables A1 - A6. The pairwise comparison fuzzy evaluation matrix under alternatives of each criterion and the pairwise comparison fuzzy evaluation matrix of criteria are listed in Tables A7 and A8. Figure 7 shows the input of FMCDM, including the fuzzy decision matrix that is the matrix of fuzzy weights of alternatives under criteria, and fuzzy weights of criteria. Figure 8 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 the other 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.

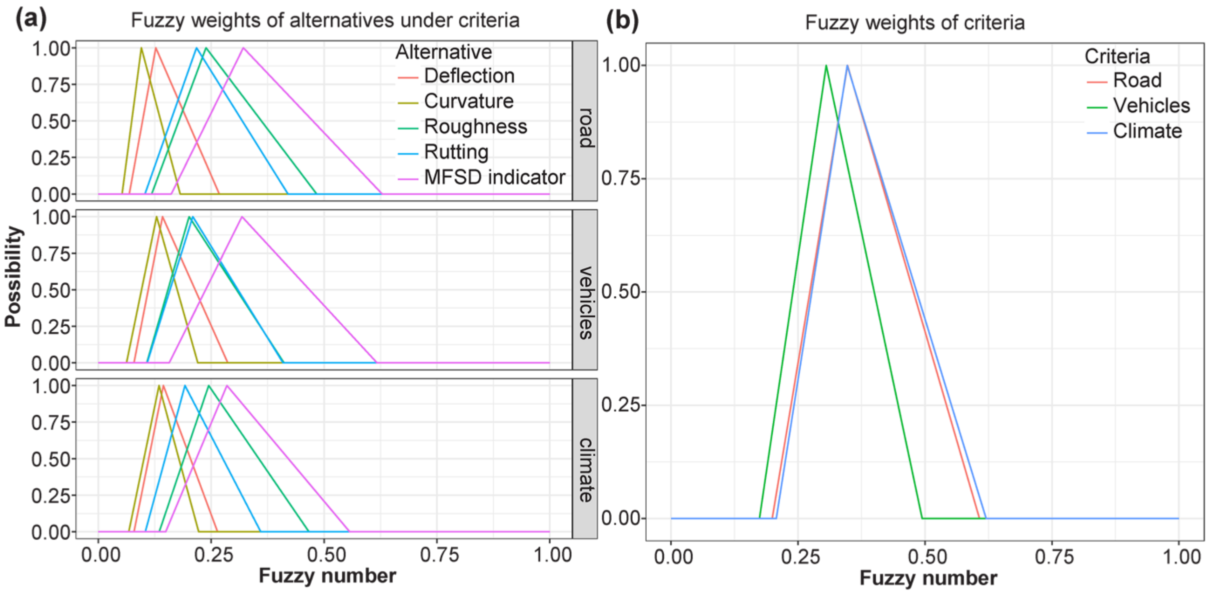

Figure 7. The input of fuzzy multi-criteria decision making: (a) fuzzy decision matrix and (b) fuzzy weights of criteria.

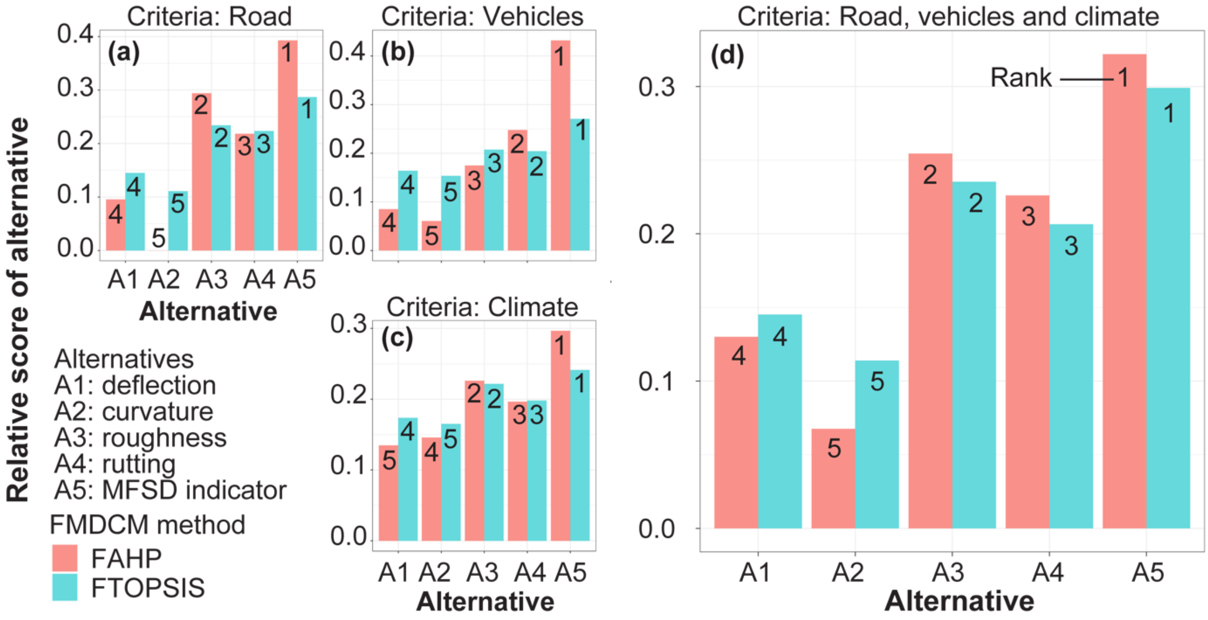

Figure 8. Relative scores and ranks of alternatives under criteria road (a), vehicles (b), climate (c) and all criteria (d).

5.4 Sensitivity analysis and evaluation

5.4.1 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 9). Both the distributions of criteria weights and the percentages of criteria weight changes are not significantly changed due to the removal of sub-criteria compared with the full model. The weight changes of 90.48% criteria are lower than 5%, and weight changes of 98.41% criteria are lower than 10%, due to the removal of each sub-criteria. Second, impacts of sub-criteria on final alternative scores are shown in Figure A7. Both FAHP and FTOPSIS analysis show that removal of each sub-criteria variable does not change the relative scores and ranks of indicator selection decisions. Finally, Figure A8 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 alternative scores. Nearly all the ranks of alternatives are not changed by removal of sub-criteria variables. The above sensitivity analysis of indicates that impacts of sub-criteria variables on the final decision making is tiny and the MFSD method is reliable for decision making.

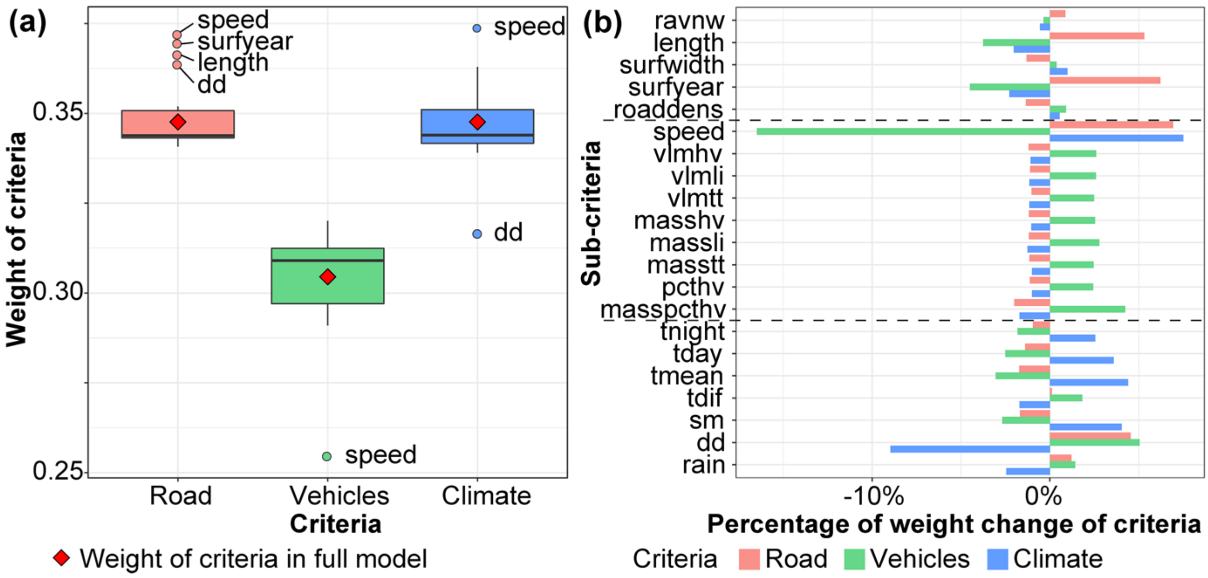

Figure 9. Criteria sensitivity analysis: (a) impacts of sub-criteria on criteria weights, where the boxes are the interquartile ranges of weights, red points are mean values, black horizontal lines are medium values, and points outside boxes are outliers; and (b) percentages of weight changes.

5.4.2 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, the impacts of contribution models on the weights of criteria and the percentages of weight changes of criteria compared with the full model are assessed (Figure 10). Results show that the changes of criteria weights due to the models are very small. The weight changes of 90.91% criteria are lower than 2%, and 100% of them are lower than 4%. Next, Figure A9 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 A10 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.

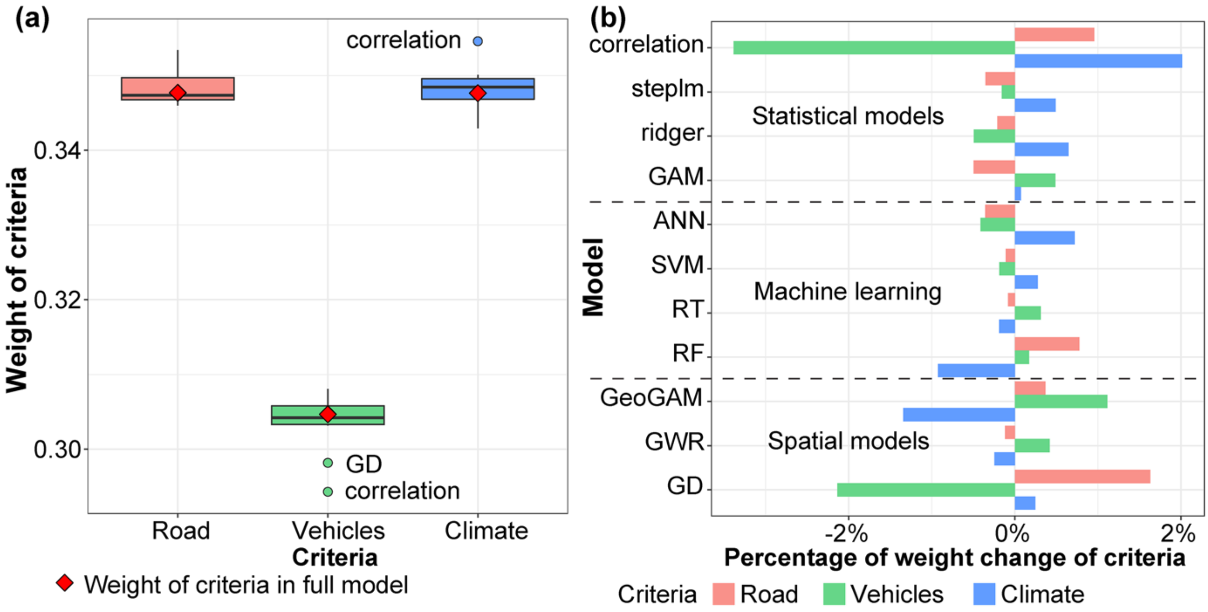

Figure 10. Sensitivity analysis of contribution models: impacts of contribution models on criteria weights (a) and percentages of criteria weight changes (b).

5.4.3 Compare indicators with road maintenance cost

To evaluate the practical performance of the indicators, they are compared with the estimated road maintenance cost in the study area in 2015 (Figure 11). 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. The correlation analysis reveals that the MFSD-based indicator and roughness are the only two indicators where their significance levels of correlations are lower than 0.01. Among the four sensor monitored indicators, roughness is the preferred choice of road performance assessment. Compared with roughness, the MFSD-based indicator can improve 30.46% of the correlation with road maintenance cost.

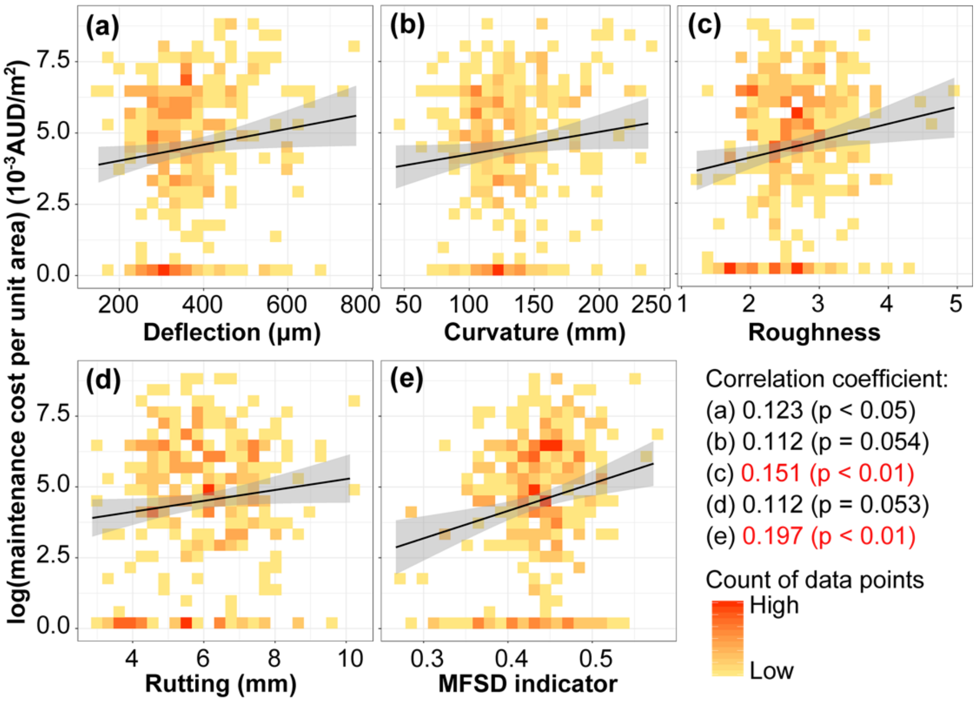

Figure 11. Relationships between real road maintenance cost and performance indicators: deflection (a), curvature (b), roughness (c), rutting (d) and MFSD-based indicator (e).

6 Discussion

This study aims to develop a comprehensive indicator to more accurately assess the sustainable road performance and evaluate burden of road maintenance. To address this issue, a MFSD approach is proposed for deriving the comprehensive road infrastructure performance indicator. The MFSD approach is developed by integrating the data-driven model-based contribution computation, fuzzy set theory, geospatial analysis and decision making and multi-criteria decision making. 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 reduce the uncertainty, potential biases and subjectivity of expert judgements and decision makers' opinions that may have impacts on the final decisions (103).
- 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. The use of multiple models can improve the accuracy and ensure the robustness of decision making.

- Fuzzy set theory is utilized to involve all the contributions of criteria computed by all models under all alternatives in the comprehensive indicator calculation and decision making. The fuzzy membership functions can involve the uncertainty of criteria contributions computed by multiple models for reliable and accurate estimations.
- 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 analyzed at the local government area level. Figure 12 shows the comparison between average MFSD-based indicator and the road maintenance cost. The result indicates that the MFSD-based indicator and the road maintenance cost are significantly correlated. At the local government area level, the MFSD-based indicator can explain 45.8% of practical road maintenance cost. The practical costs of road maintenance are also associated with diverse factors, such as the severity of road defects, labour costs and the use of different maintenance equipment. The local government areas are divided into six groups in terms of their relative locations along the six primary roads. Regions along Brand Highway have the lowest burden of road maintenance.

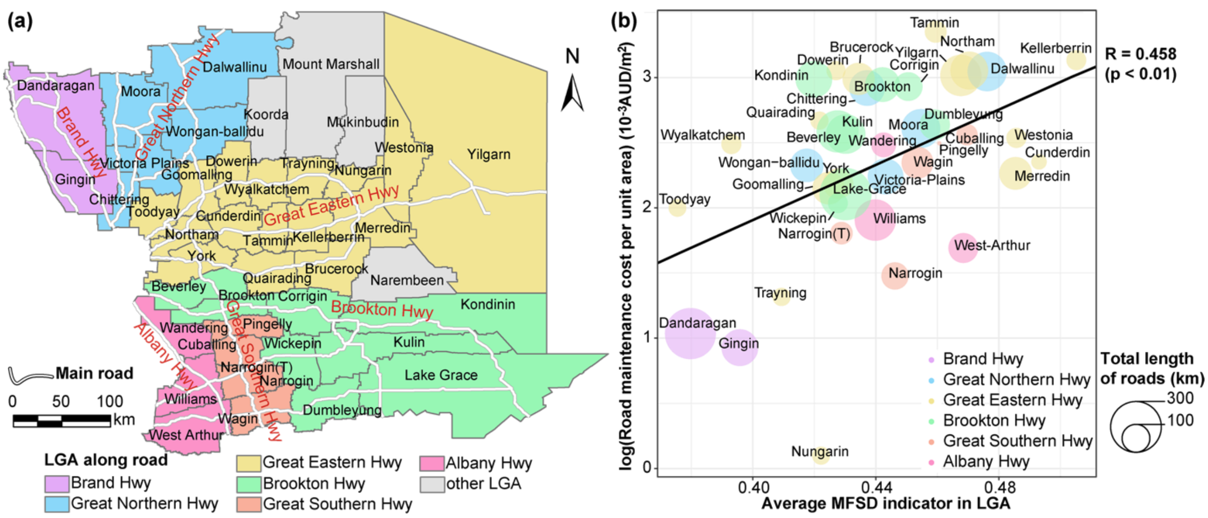

Figure 12. Comparison between average MFSD-based indicator and the road maintenance cost in local government areas.

There are still limitations in the study and future relevant studies are recommended from following aspects. Frist, the accuracy and effectiveness of the MFSD method in evaluating road performance can be compared with emerging technologies that have been applied in industries, if required datasets are available in study areas. The emerging technologies include various pavement conditioning indexes (104, 105), MicroPAVER software (106, 107), deep learning (108) and image processing approaches (109). In addition, it is recommended to investigate the relationship between road performance indicators and the severity of defects to more accurately reveal the burden for road maintenance.

7 Conclusion

This study proposes an MFSD method for deriving a geographically local, comprehensive and accurate indicator of sustainable road infrastructure performance. The comprehensive MFSD-based indicator contains information of both sensors monitored indicators and potential factors of road performance. In the study area, the MFSD-based indicator can improve 30.46% of the correlation with road maintenance cost compared with roughness, which is the optimal sensor monitored indicator. The MFSD-based indicator indicates that 19.23% of roads in the network are of very high burden of road maintenance. The sensitivity analysis indicates that the MFSD is a reliable decision making approach, where contribution computation models and potential factor variables have limited impacts on final decisions. Thus, data and models driven approaches can critically improve the accuracy and effectiveness of practical decision making. Results in this study can provide informative knowledge and quantitative evidence for the practical decision making of traffic environment assessment, road performance monitoring design and evaluation, and road maintenance and management. In addition to the traffic and road problems, the MFSD method also has wide and great potentials in addressing geospatial decision making issues in other fields, such as environment and public health.

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Competing Interests

The authors have declared that they have no completing interests.

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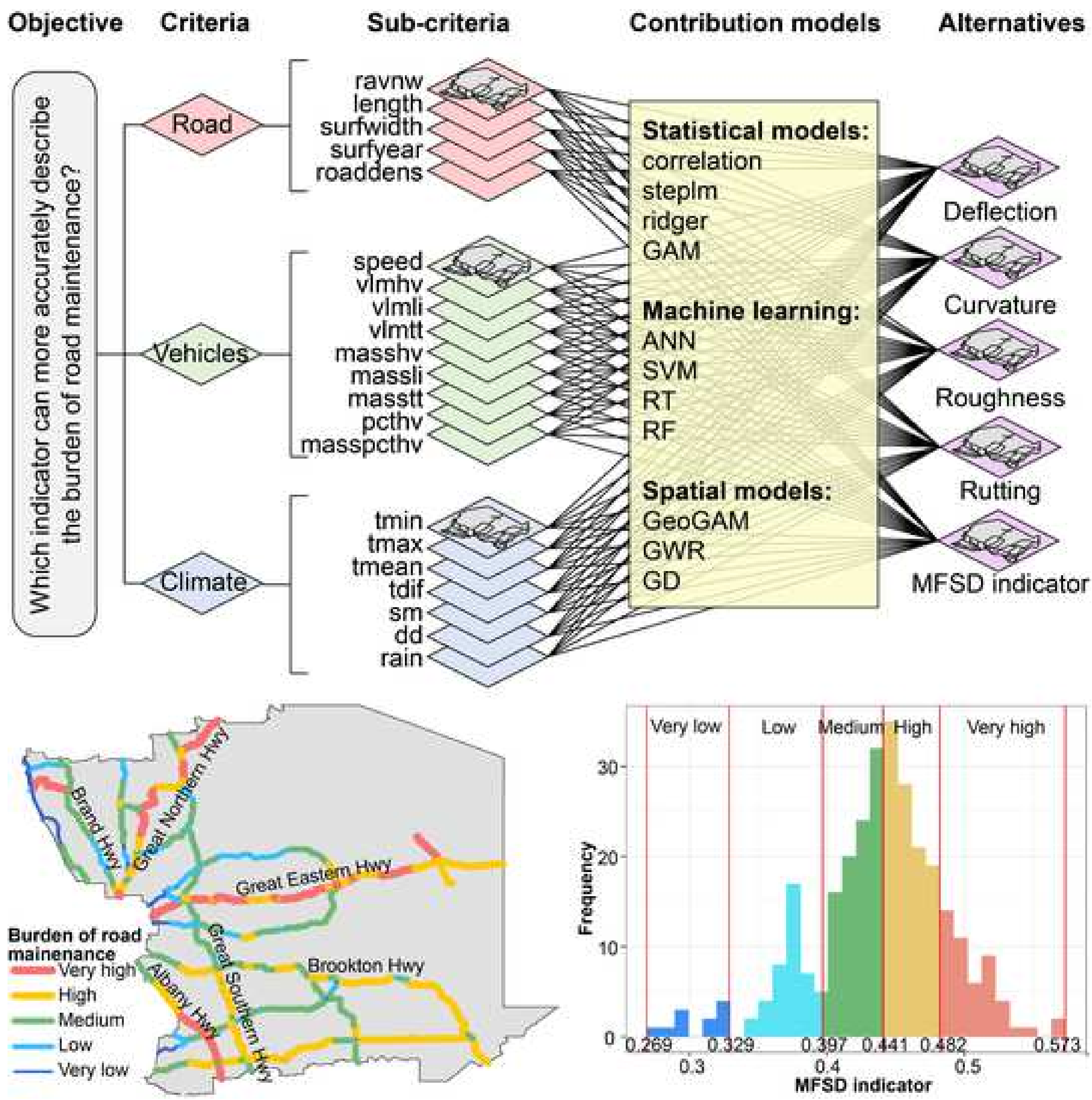
Graph Abstract



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Sustainable road infrastructure maintenance using a model-driven fuzzy spatial multi-criteria decision making method

Include:

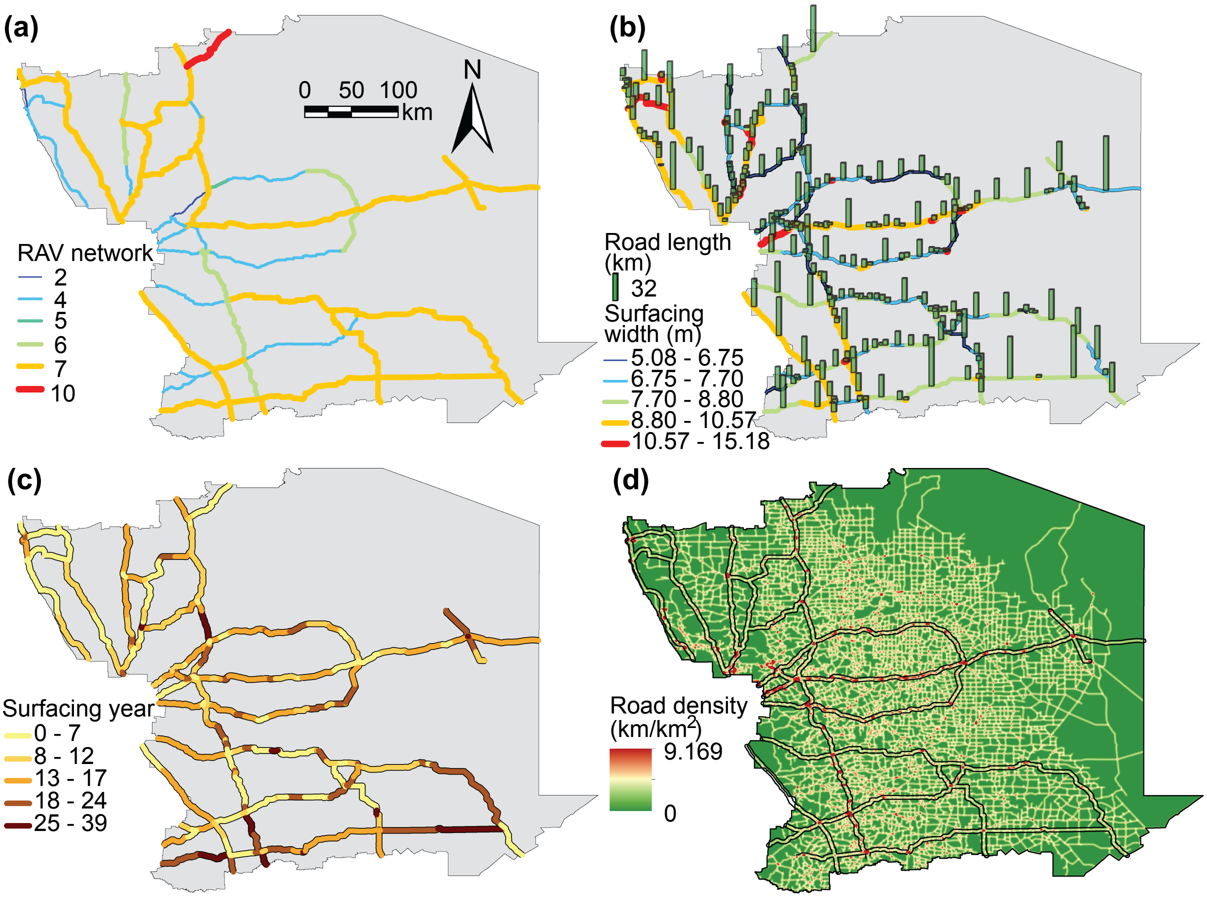

Figure A1. Spatial distributions of variables of road characteristics.

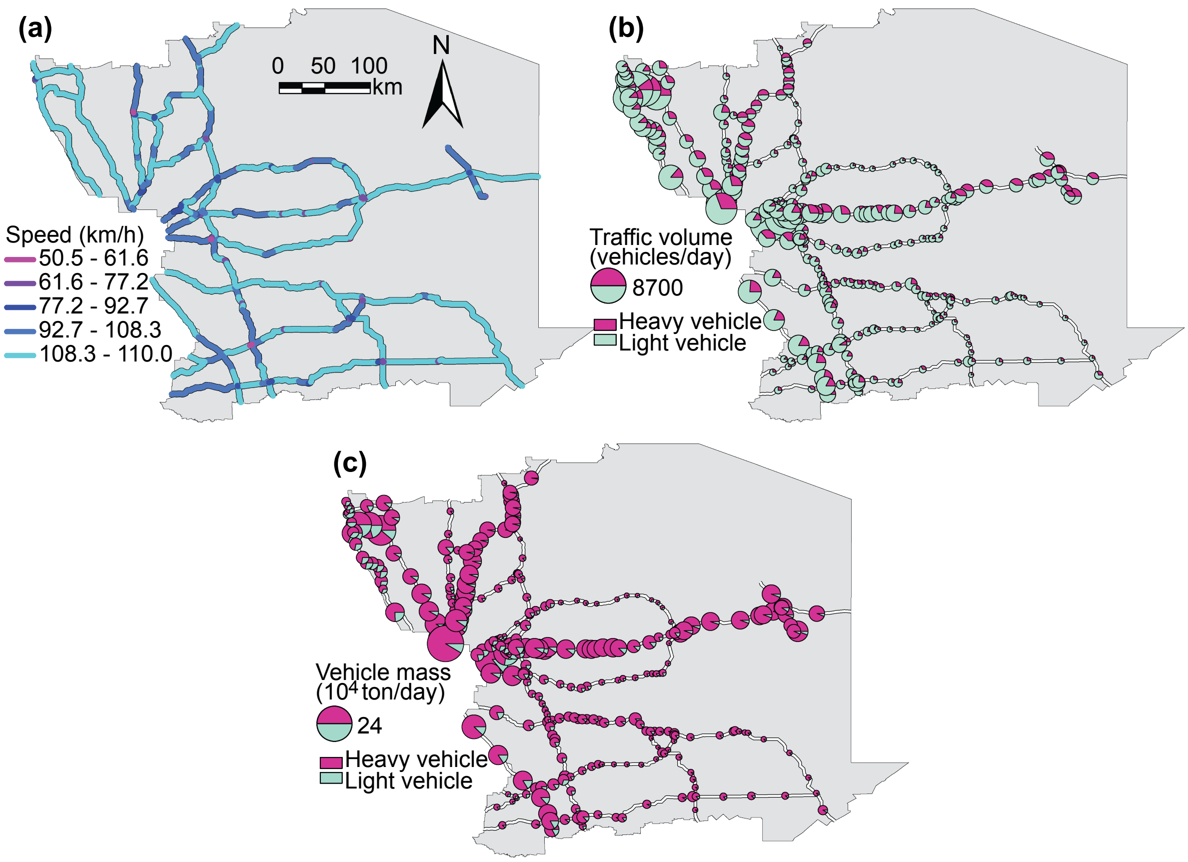

Figure A2. Spatial distributions of variables of vehicles and traffic conditions.

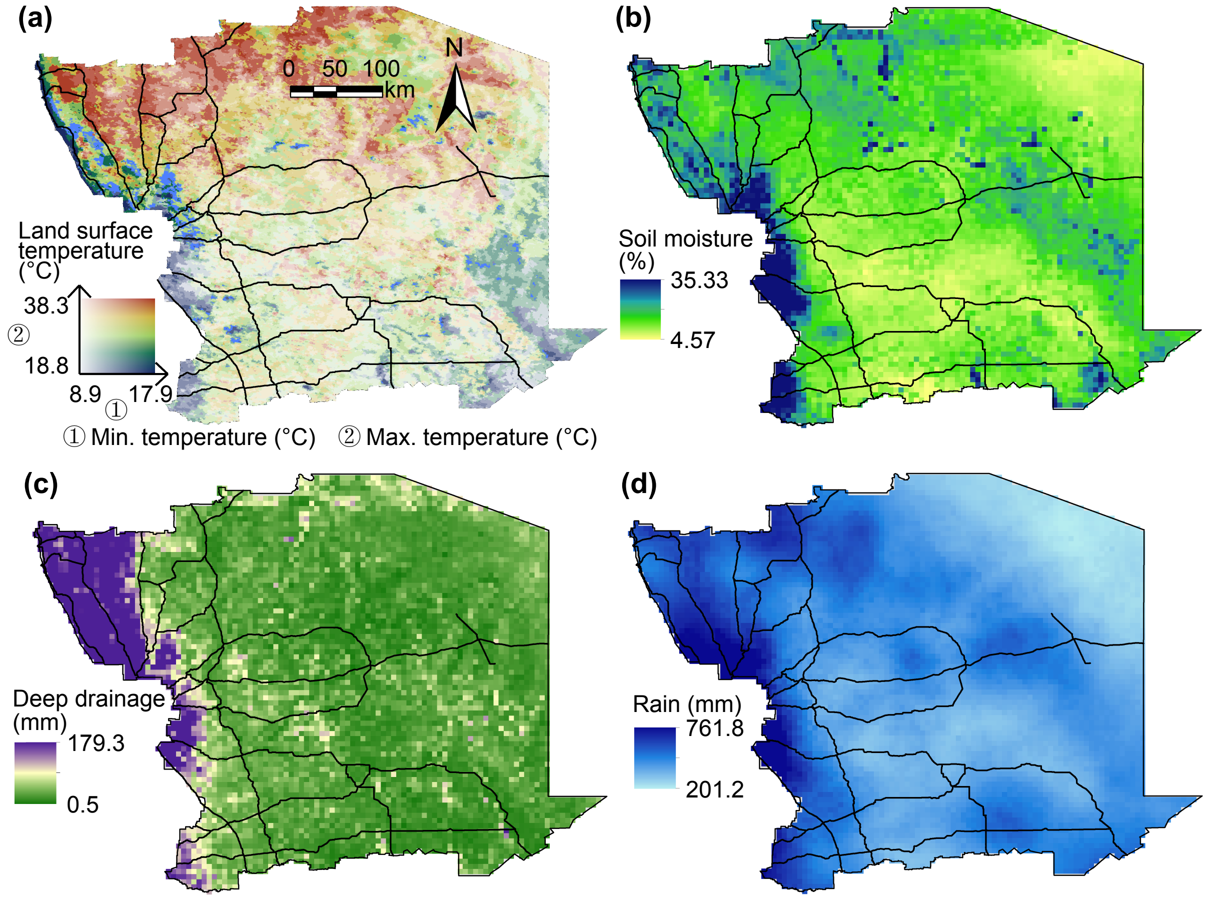

Figure A3. Spatial distributions of variables of climate and environmental conditions.

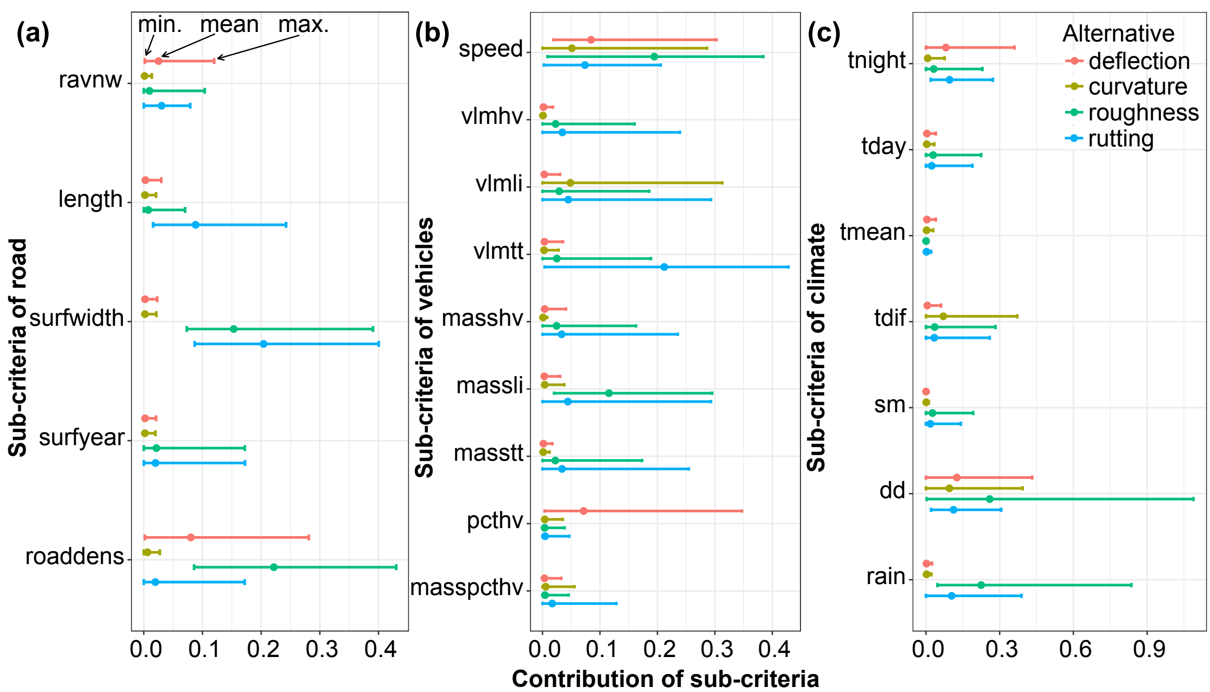

Figure A4. Summary of model-based contributions of sub-criteria on alternatives

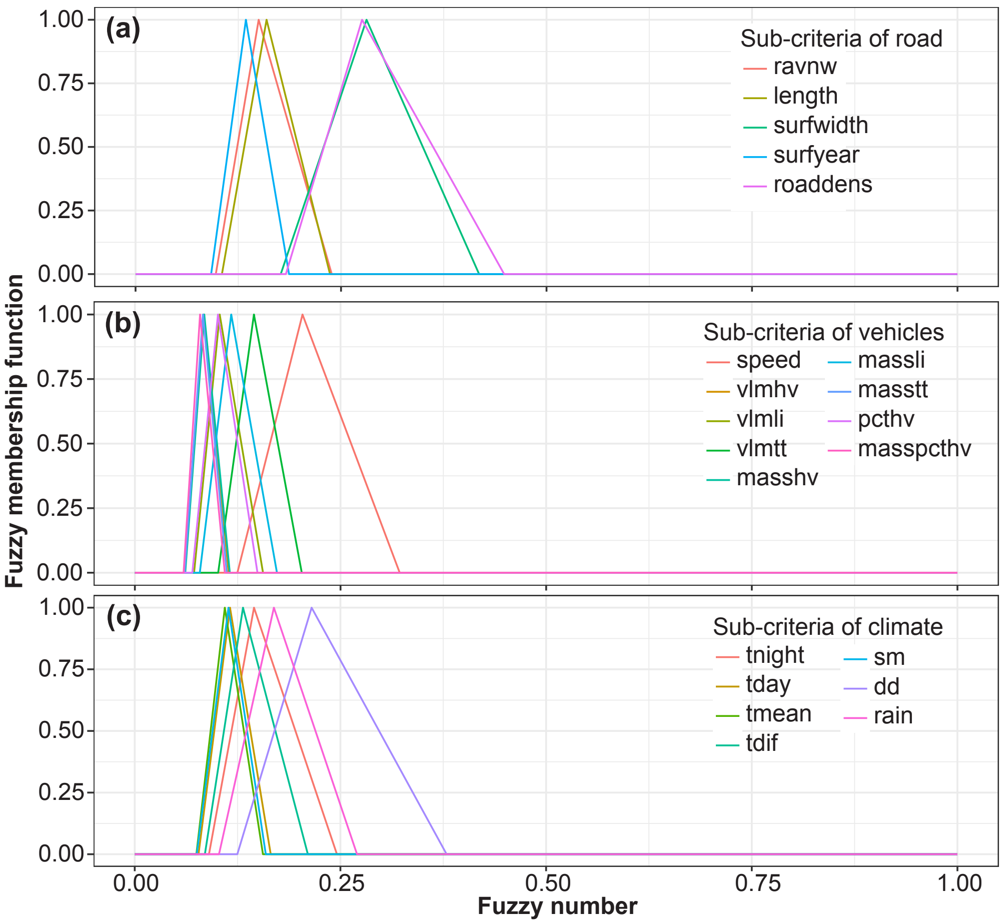

Figure A5. Fuzzy membership functions of sub-criteria of each criterion.

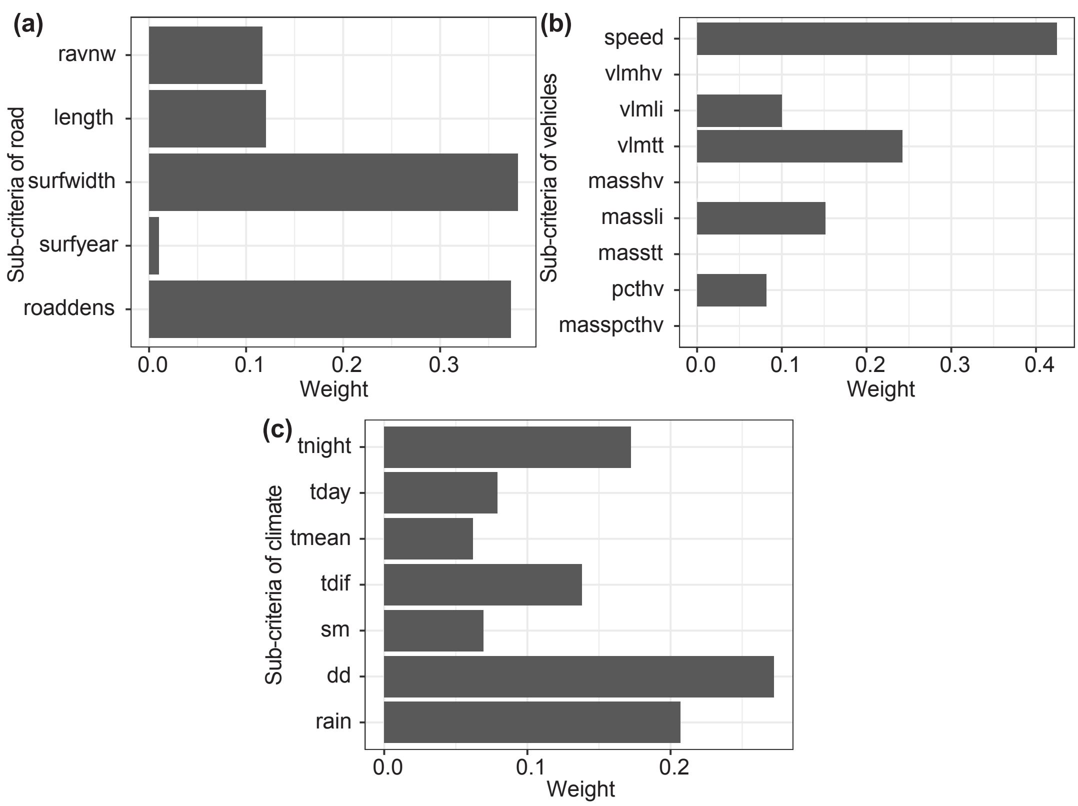

Figure A6. Weights of sub-criteria for MFSD-based indicator.

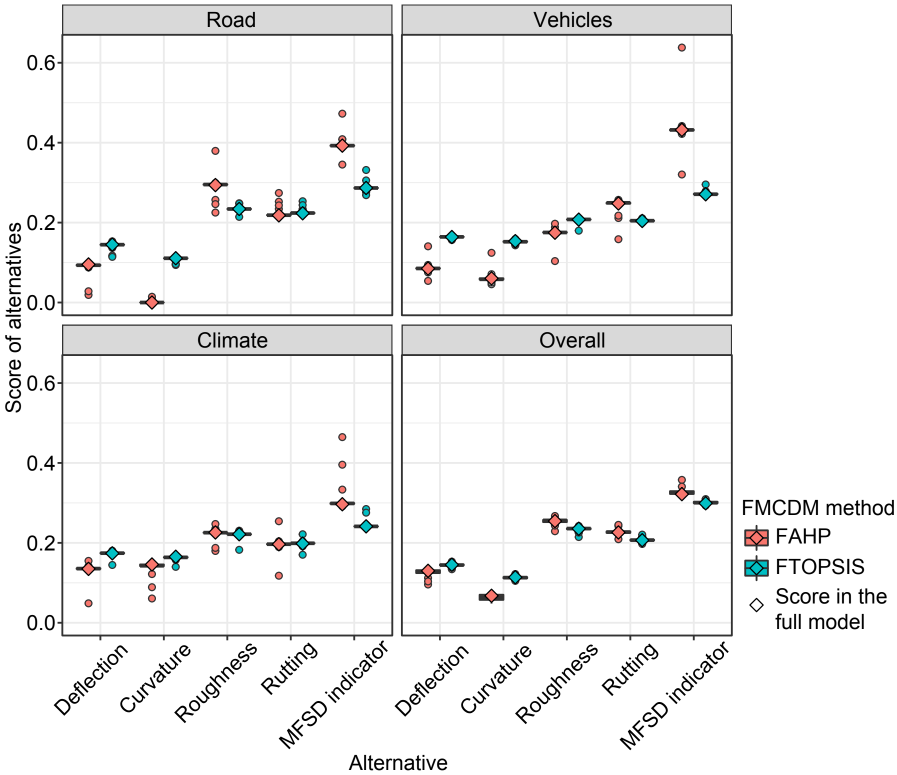

Figure A7. Sensitivity analysis of criteria: impacts of sub-criteria on the scores from the sectors of road, vehicles and climate, and the overall scores of alternatives.

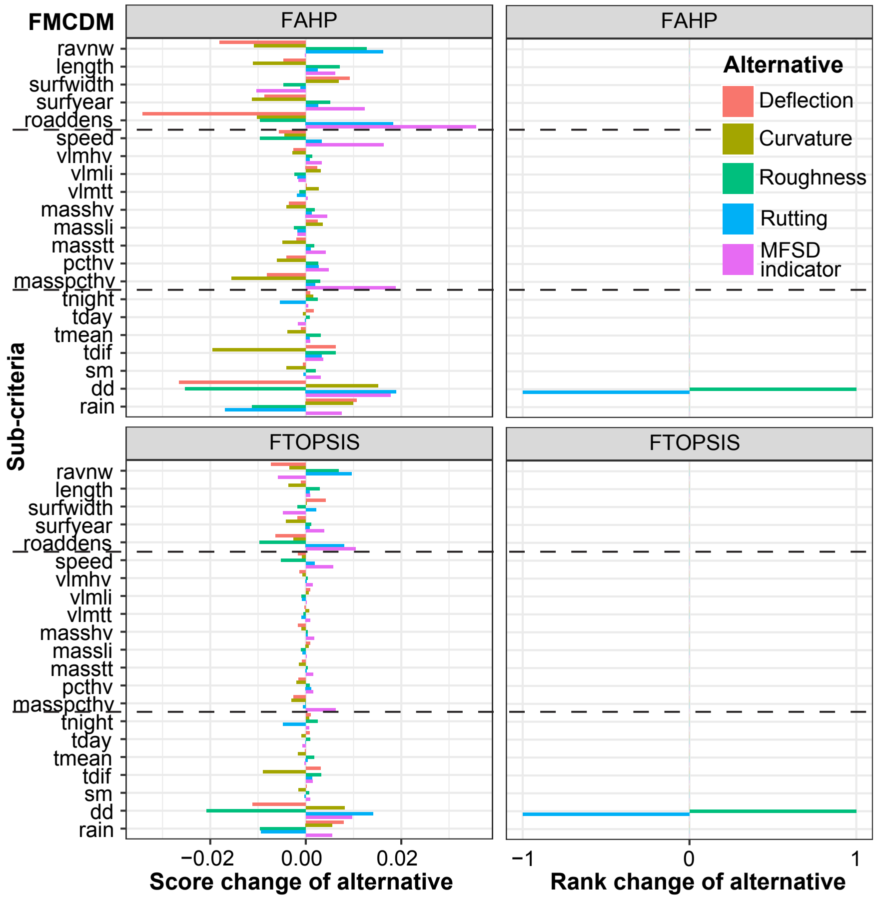

Figure A8. Sensitivity analysis of criteria: impacts of sub-criteria on the overall score and rank changes of alternatives compared with the full model.

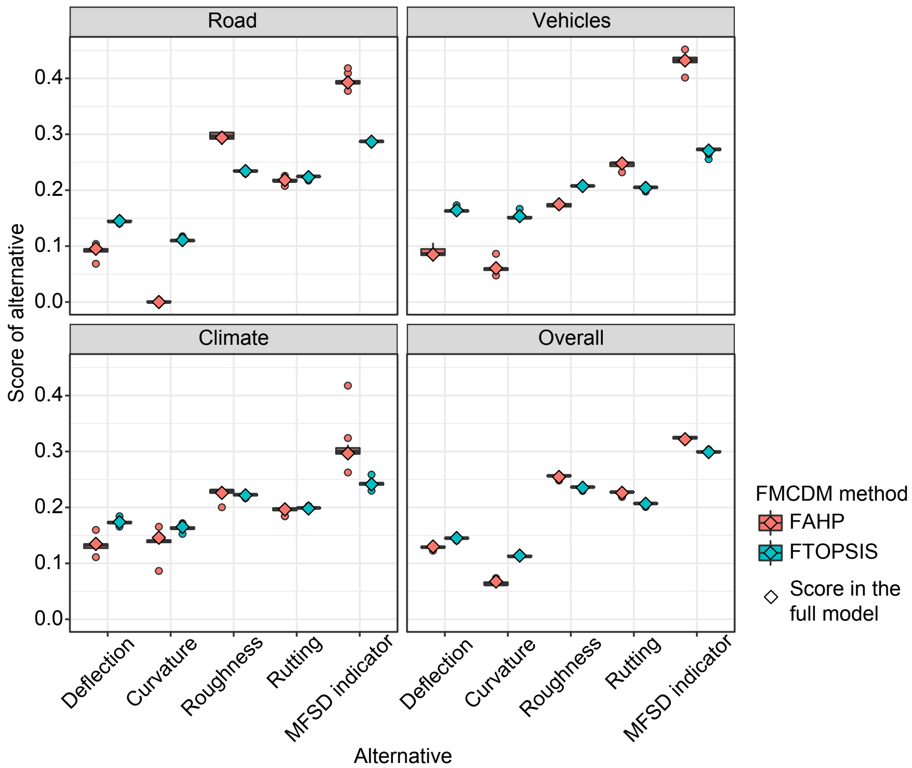

Figure A9. Sensitivity analysis of contribution models: impacts of contribution models on the scores from the sectors of road, vehicles and climate, and the overall scores of alternatives.

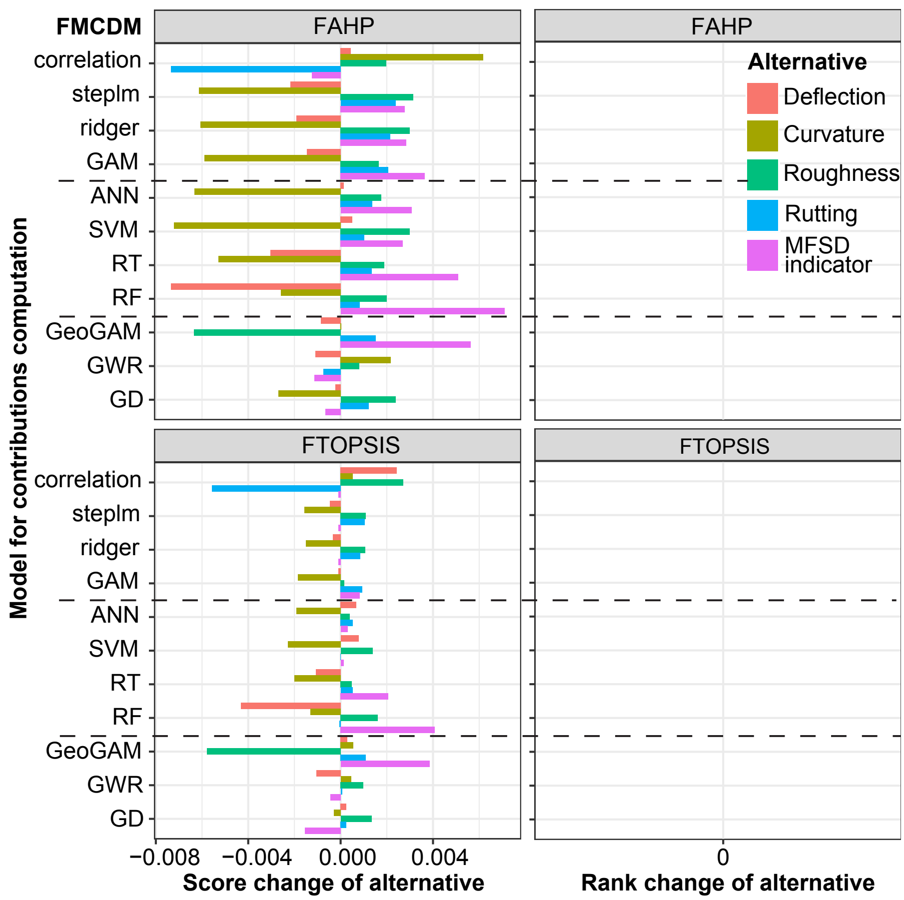

Figure A10. Sensitivity analysis of contribution models: impacts of contribution models on the overall score and rank changes of alternatives compared with the full model.

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1 Criteria selection and data pre-processing

The normalization function of a variable X is:

$$f(X) = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{A1}$$

or

$$f(X) = \frac{\max(X) - X}{\max(X) - \min(X)} \tag{A2}$$

where equation (A1) is for positively related variables and equation (A2) is for negatively related variables associated with the study objective.

Two methods are available to select variables statistically correlated with alternatives to remove variables without significant correlations. One 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 et al., 2017). The collinearities among variables can be diagnosed using the variance inflation factors (VIFs). In general, when VIF is larger than 4, the variable should be removed due to the 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).

2 Model-based contributions of criteria

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 relationships. **Correlation analysis** examines the contributions of variables to alternatives by correlation coefficients and corresponding significance levels. In general, the range of correlation coefficient is [-1, 1], where the negative value indicates negative association, positive value indicates positive association, and 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** equals to linear regression if the variables are selected using the step-wise linear regression in the variable selection period. **Ridge regression** is a robust regression method that can avoid overfitting and multi-collinearity without removing predictor variables (Hoerl and Kennard, 1970b, Hoerl and Kennard, 1970a, Marquaridt, 1970). The R *glmnet* package is used for the computation of ridge regression, where cross validation is used to determine the tuning parameter that controls the strength of the penalty term (Friedman et al., 2010). **GAM** is a widely used nonlinear regression model. In GAM, the nonlinear relationships between variables and responses are described through nonparametric smoothing functions (Hastie and Tibshirani, 1990). The R *mgcv* package is used for GAM calculation (Wood, 2017, Wood, 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).

Machine learning algorithms used in the study are artificial neural network (ANN), support vector machine (SVM), 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 a large amount of highly interconnected artificial neurons and weighted links among input and output data (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. In this study, the ANN analysis is performed using the 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 also called support vector regression (SVR) model, to determine the best regression function, a hyperplane is constructed to maximize the margin (the distance between hyperplane to the nearest data point), and to minimize the regression error (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 set of decision rules on the explanatory variables by recursively partitioning the data into ordered smaller groups with binary splits based on a single 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 selected split is the one with maximum homogeneity of the two final groups regarding the response variable. The RT model is run by R *rpart* package (Therneau et al., 2018). **RF** constructs a multitude of decision trees during training and outputs the mean prediction of the individual trees for regression (Ho, 1995, Barandiaran, 1998). The trees grow from a random subset of variables at each splitting node, and they can grow without trim. The trees grow independently to the maximum size based on a bootstrap sample of training data, then the remaining samples are used for calculating the unbiased out-of-bag error rate and the relative importance of variables (Breiman, 2001, Prasad et al., 2006). RF is robust to noise in data, overfitting problems and small sample sizes, and requires minimal manual parameterization (Rodriguez-Galiano et al., 2012). The RF analysis is run with the R *randomForest* package (Liaw and Wiener, 2002). The above four models can provide an overall contribution of all selected variables in the models and the respective relative importance of variables, then the contribution of variable x_i $(i = 1, \ldots, n)$ is computed using the equation:

$$\beta_i = \beta_0 \cdot \frac{r_i}{\sum_i r_i} \tag{A3}$$

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

Spatial analysis models consist of geospatial generalized additive model (GeoGAM), 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 et al., 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, Wood, 2003). **GWR** is a critical local method to investigate geospatial non-stationarity of data relationships (Brunsdon et al., 1996, Fotheringham et al., 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 et al., 2003, Fotheringham, 2000). In this study, the contributions of variables are calculated with the total fitness of GWR model and the mean local coefficients of variables. **GD** is a spatial statistical model for the analysis of spatial data relationships in terms of spatial variance of variables and geographical strata (Wang et al., 2014, Wang et al., 2010, Wang et al., 2016). Since the contributions of variables are fully determined by the variance and geographical strata, no linear assumptions and collinearity tests are required for a single variable and pairs of variables (Wang, 2017, Song et al., 2018). In this study, GD model is run by the R *GD* package (Song et al., 2020).

3 Fuzzy set theory

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

$$\Phi = \{x, \mu_\Phi(x)\}, x \in R \tag{A4}$$

where μ_Φ is the membership function that presents the degree of membership of fuzzy set Φ to the data space R (Chang, 1996). A fuzzy number M on the data space R can be defined as a triangular fuzzy number, and its membership function is denoted by (l, m, u), where $l \leq m \leq u$, and they stand for the lower value, most possible value and upper value, respectively (Kahraman et al., 2003). Then, the equation of the membership function is:

$$\mu_M(x) = \begin{cases} 0 & x < l \\ \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0 & x > u \end{cases} \tag{A5}$$

4 Fuzzy MCDM in MFSD approach

4.1 Fuzzy analytical hierarchy process (FAHP)

In the MFSD approach, the FAHP is utilized both for computing the comprehensive indicator for mapping road maintenance burden, and for the decision making for ranking alternatives. Once the model-based contributions of criteria are computed as triangular fuzzy numbers, the triangular fuzzy comparison matrix is formed as:

$$(\mathrm{D})_{p\times p} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1q}, m_{1q}, u_{1q}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \cdots & (l_{2q}, m_{2q}, u_{2q}) \\ \vdots & \vdots & \ddots & \vdots \\ (l_{q1}, m_{q1}, u_{q1}) & (l_{q2}, m_{q2}, u_{q2}) & \cdots & (1,1,1) \end{bmatrix}_{p\times p} \tag{A6}$$

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 i equals j, $\mathrm{D}_{ij} = (1,1,1)$. 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 et al., 2009), but they are continuous real numbers within the above ranges in the model-based decision making in this study.

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

$$(B_i')_{1\times(p\times v)} = [\beta_{11}', \ldots, \beta_{1v}', \beta_{21}' \ldots, \beta_{2v}', \ldots, \beta_{p1}', \ldots, \beta_{pv}']_{1\times(p\times v)} \quad \text{(A7)}$$

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

$$(B_i)_{1\times(p\times v)} = [\beta_{11}, \ldots, \beta_{pv}]_{\ 1\times(p\times v)} \quad \text{(A8)}$$

where $\beta_{jk} (j = 1, \ldots, p; k = 1, \ldots, v)$ 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:

$$T = (l^T, m^T, u^T) = \begin{cases} (1,1,1) & \beta = 1 \\ (1, \beta, \beta + 1) & 1 < \beta \le 2 \\ (\beta - 1, \beta, \beta + 1) & 2 < \beta \le 8 \\ (\beta - 1, \beta, \beta) & 8 < \beta \le 9 \end{cases} \quad \text{(A9)}$$

where $T = (1,1,1)$ indicates the variables are equally important, and 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:

$$S_i = \sum_{i=1}^{q} D_{ij} \otimes \left[\sum_{j=1}^{q} \sum_{i=1}^{q} D_{ij}\right]^{-1} \quad \text{(A10)}$$

In terms of the operation laws of equations (A6) - (A9), the fuzzy triangular number S_i can be calculated as:

$$S_i = \left(\frac{\sum_{i=1}^{q} l_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} u_{ij}}, \frac{\sum_{i=1}^{q} m_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} m_{ij}}, \frac{\sum_{i=1}^{q} u_{ij}}{\sum_{j=1}^{q} \sum_{i=1}^{q} l_{ij}} \right) \quad \text{(A11)}$$

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

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

$$V(M_1 \ge M_2) = \begin{cases} 1 & m_1 \ge m_2 \\ hgt(M_1 \cap M_2) = \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)} & m_1 < m_2 \end{cases} \quad \text{(A12)}$$

where $hgt(M_1 \cap M_2)$ is the highest interaction between two membership functions (Chang, 1996). To compare two membership functions, the values of both $V(M_1 \ge M_2)$ and

$V(M_2 \geq M_1)$ should be calculated. Then, the degree of possibility for a convex fuzzy number to be larger than k convex fuzzy numbers $M_i (i = 1,2, \ldots, k)$ is calculated by:

$$V(M \geq M_1, M_2, \ldots, M_k) = \min\big(V(M \geq M_i)\big) \tag{A13}$$

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

$$w'^{A}(a_i) = \min(S_i \geq S_k)\,; k = 1,2, \ldots, p; k \neq i \tag{A14}$$

and the weight vector of alternatives is:

$$w'^{\mathrm{A}} = [w'(a_1), w'(a_2), \ldots, w'\big(a_p\big)]^T \tag{A15}$$

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

$$w^{A} = [w(a_1), w(a_2), \ldots, w\big(a_p\big)]^T \tag{A16}$$

where w^A is a non-fuzzy number.

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

In the MFSD-based decision making process, the ranking of alternatives is determined by the comparison study using both FAHP and FTOPSIS. TOPSIS defines that the optimal alternative should be closely approximate the expected solution and far from the rejected ones (Opricovic and Tzeng, 2004, Hwang and Yoon, 1981). The distance between two triangular fuzzy numbers $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ is calculated using the vertex method with the equation:

$$d(M_1, M_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \tag{A17}$$

In the study, the weights of criteria in FTOPSIS stage are also derived from the model-based contributions of criteria. Different from FAHP that the aggregated fuzzy rating of alternatives and fuzzy weights of criteria are computed using pair-wise comparison of triangular fuzzy numbers, FTOPSIS computes the values separately for the respective models. The fuzzy rating of alternative $A_i (i = 1, \ldots, p)$ under criterion $C_j (j = 1, \ldots, q)$ computed by model $G_k (k = 1, \ldots, v)$ 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:

$$l_{ij} = \min_k(l_{ij}^k)\,, m_{ij} = \frac{1}{v}\sum_{k=1}^{v} m_{ij}^k\,, u_{ij} = \max_k(u_{ij}^k) \tag{A18}$$

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

$$w_{j1}^C = \min_k(w_{j1}^k)\,, w_{j2}^C = \frac{1}{v}\sum_{k=1}^{v} w_{j2}^k\,, w_{j3}^C = \max_k(w_{j3}^k) \tag{A19}$$

Through a linear scale transformation, the fuzzy decision matrix can be normalized as:

$$(\mathrm{R})_{p \times q} = (r_{ij})_{p \times q}; i = 1, \ldots, p; j = 1, \ldots, q \tag{A20}$$

where

$$\text{for the benefit criteria:} \begin{cases} r_{ij} = (\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}) \\ u_j^* = \max_i(u_{ij}) \end{cases} \quad \text{(A21)}$$

or

$$\text{for the cost criteria:} \begin{cases} r_{ij} = (\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}) \\ l_j^- = \min_i(l_{ij}) \end{cases} \quad \text{(A22)}$$

The weighted normalized fuzzy decision matrix is calculated by multiplying the normalized fuzzy decision matrix with the weights of criteria:

$$(\mathrm{H})_{p\times q} = [(l_{ij}^H, m_{ij}^H, u_{ij}^H)]_{p\times q} = [h_{ij}]_{p\times q} = r_{ij} \times w_j \quad \text{(A23)}$$

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

$$\text{FPIS: } A^* = (h_1^*, h_2^*, \dots, h_q^*), \text{ where } h_j^* = \max_i(u_{ij}^H) \quad \text{(A24)}$$

$$\text{FNIS: } A^- = (h_1^-, h_2^-, \dots, h_q^-), \text{ where } h_j^- = \min_i(l_{ij}^H) \quad \text{(A25)}$$

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

$$\text{Distance to FPIS: } d_i^* = \sum_{j=1}^{q} d^H(h_{ij}, h_j^*) \quad \text{(A26)}$$

$$\text{Distance to FNIS: } d_i^- = \sum_{j=1}^{q} d^H(h_{ij}, h_j^-) \quad \text{(A27)}$$

where $d^H(M_1, M_2)$ is the distance between two triangular fuzzy numbers 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:

$$\theta_i = \frac{d_i^-}{d_i^- + d_i^*} \quad \text{(A28)}$$

The alternative with the highest closeness coefficient is regarded as the best alternative. 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).

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Supplementary Information – Tables for

Sustainable road infrastructure maintenance using a model-driven fuzzy spatial multi-criteria decision making method

Include:

Supplementary Table A1

Supplementary Table A2

Supplementary Table A3

Supplementary Table A4

Supplementary Table A5

Supplementary Table A6

Supplementary Table A7

Supplementary Table A8

Table A1. 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 A2. 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 A3. 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 A4. 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 A5. 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 A6. Pairwise comparison fuzzy evaluation matrix of sub-criteria of climate.

	tnight	tday	tmean	tdif	sm
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)
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)
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)
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)
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)
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)
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)

	dd	rain
tnight	(0.649,0.993,1.451)	(0.818,1.135,1.592)
tday	(0.523,0.758,0.993)	(0.734,0.911,1.226)
tmean	(0.512,0.699,0.935)	(0.651,0.802,1.065)
tdif	(0.697,1.062,1.504)	(0.875,1.169,1.699)
sm	(0.491,0.708,0.903)	(0.638,0.822,1.072)
dd	(1,1,1)	(0.97,1.359,2.102)
rain	(0.661,1.058,1.504)	(1,1,1)

Table A7. 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 A8. 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)