# A Spatial Heterogeneity-Based Segmentation Model for Analyzing Road Deterioration Network Data in Multi-Scale Infrastructure Systems

Yongze Song, *Member, IEEE*, Peng Wu, Daniel Gilmore, and Qindong Li

***Abstract*— Road network conditions and road quality are directly linked with the performance of an entire infrastructure system. As sensor monitoring of road deteriorations has rapidly increased, road infrastructure performance can now be assessed using multiple measures. However, more effective and accurate quantitative analysis methods are increasingly required. This research explores road infrastructure performance using road deterioration network data in the Mid West Gascoyne region, Australia. A spatial heterogeneity-based segmentation (SHS) model is developed for redefining road segments across the network in terms of sensor monitoring data, and for both project-level and network-level infrastructure systems management. To evaluate the model effectiveness and accuracy, an evaluation system is proposed from four aspects: segment number, homogeneity within segments, heterogeneity among segments, and segment morphology. The SHS model is compared with two widely used road network segmentation methods. The results show that the SHS model can use fewer segments to ensure higher homogeneity within segments and heterogeneity among segments across the network. Meanwhile, the segment lengths are more uniformly distributed as compared with results from other methods. The developed model and findings from this research can significantly improve the utilization of sensor monitoring network data and support multi-scale infrastructure systems management.**

***Index Terms*— Smart infrastructure management, road network, road deterioration, spatial heterogeneity, GIS, spatial analysis.**

## I. INTRODUCTION

A ROAD network is one of the core components of an infrastructure system [1], [2]. A critical function of the road network is to link buildings, transport facilities, and other facilities of the infrastructure system, such as energy, water, health, and waste facilities [3], [4]. Therefore, the road network conditions and effectiveness have essential impacts on the performance of the entire infrastructure system. Sensor monitoring data has been increasingly accumulated for road performance assessment [5], [6]. However, the methods are still limited insofar as effective, accurate, and large spatial scale infrastructure data analysis.

In general, a road surface condition can be measured using the traffic burden, pavement service life, and deterioration. The traffic burden is computed as the sum weight of all types of vehicles, where heavy and light vehicles are the primary types. Studies in various nations show that light vehicles are much more common than heavy vehicles, but more than 80% of the traffic burden on the road surface comes from heavy vehicles [7]. In addition, the pavement service life is a widely used indicator for practical road design, construction, maintenance, and decision-making [8]–[10]. The pavement service life is associated with the design life, variations of traffic flows, and local environmental conditions, so it is usually not significantly correlated with real conditions. Road deterioration includes various movements, wear and tear, and structural and physical damage [11]. The rapidly increased usage of sensor monitoring data for road deterioration brings more opportunities to quantitatively assess road surface conditions [12]–[14]. In this study, road conditions are investigated using sensor monitoring deterioration network data.

Road infrastructure data analysis methods generally come from three categories of current and practically urgent requirements. First, network-level management has become as important as project-level management. Owing to the high accuracy of sensors, road condition data has been widely used in local road construction and maintenance projects, and in project-level management. For instance, the spatial distribution of road deterioration has been predicted for roads in New York, USA [15], and road condition future scenarios have been predicted for fifteen low-volume roads in Kerala, India [16]. With the accumulation of data, data-driven investigations, especially large spatial scale data analysis methods, have become more important for network-level infrastructure management, such as state, regional, and national level decision-making [17]–[19]. Another concern is providing in-depth data analysis for simultaneously satisfying different road users' requirements. In practice, raw observations generally reveal the exact and local conditions within a short road, but segment-based data are more practical for real construction works and management [20]. For instance, project-level summaries

Manuscript received October 17, 2019; revised April 19, 2020; accepted June 3, 2020. This work was supported by the Australian Government through the Australian Research Council's Discovery Project under Project DP180104026. The Associate Editor for this article was C. G. Claudel. *(Corresponding author: Peng Wu.)*

Yongze Song is with the School of Design and the Built Environment, Curtin University, Perth, WA 6102, Australia (e-mail: yongze.song@curtin.edu.au).

Peng Wu is with the Department of Construction Management, School of Design and the Built Environment, Curtin University, Perth, WA 6102, Australia (e-mail: peng.wu@curtin.edu.au).

Daniel Gilmore and Qindong Li are with the Head Office - Don Aitken Centre, Main Roads Western Australia, Perth, WA 6004, Australia (e-mail: Daniel.Gilmore@mainroads.wa.gov.au; qindong.li@mainroads.wa.gov.au).

Digital Object Identifier 10.1109/TITS.2020.3001193

can indicate the requirements or effects of construction and maintenance activities, and network-level summaries can be used in strategic road infrastructure investment and management. Therefore, there is great practical potential in developing data analysis methods for multi-scale infrastructure systems. Finally, the improvement of data accuracy requires improvements in modeling accuracy and effectiveness. At the same time, the question of how to quantitatively evaluate the accuracy and effectiveness of different methods remains an open issue.

Spatial heterogeneity models have advantages in flexibly segmenting spatial data in both large and local spatial scales. For instance, in terms of spatial heterogeneity within geographical image data, landscape products and remote sensing data can be segmented in multiple scales [21]–[23]. Among the models, the spatial stratified heterogeneity approach is widely utilized for assessing spatial heterogeneity among strata defined by spatial explanatory variables in geosciences [24]–[26]. However, few knowledges are available about integrating spatial heterogeneity and characteristics of line segments on road network to address road deterioration issues.

This study develops a spatial heterogeneity-based segmentation (SHS) model for investigating road performance from both project and network levels for multi-scale infrastructure systems. High-resolution road deterioration data, including curvature and deflection data, are collected across the entire network in the Mid-West Gascoyne region of Australia. The SHS model is developed and utilized for the homogeneous segmentation of deterioration network data. In addition, an evaluation system is proposed to compare the effectiveness of the SHS model and other two homogeneous segmentation methods, i.e., the cumulative difference approach (CDA) and the minimization coefficient of variation (MCV) method. Finally, the segmentation results are applied to a risk evolution for road infrastructure systems.

## II. Related Works

Methods related to this study are reviewed in this section, including methods for road segment definition and homogeneous segmentation.

### A. Road Segment Definitions

In construction works and network management, a road segment is generally defined in three ways. First, a road segment can be a specific part of a road located between two intersections [27], [28]. In this way, the road segments are determined by road number, name, direction, and intersection locations in a road network. Another approach for defining a road segment is to find a part of a road with uniform properties, such as an identical number of lanes, width, pavement surfacing type, construction material, or soil type. In practice and in data analysis, road segments are identified using categorical variables. The final definition considers that a road segment usually has similar or approximate characteristics, including traffic flows, road deteriorations, and local environmental conditions [29], [30]. Road deteriorations are reflected in sensor monitoring data, including curvature, deflection, roughness, and rutting. Local environmental conditions, such as temperature, precipitation, and soil moisture, can be measured with ground sensors and satellite remote sensing. This definition presents road segments using continuous observations of road or traffic variables. The rapidly increased multi-source sensor data provides more opportunities and potential for using the last definition in data analysis, traffic flow prediction, and road infrastructure management. The above three definitions have their respective advantages. Thus, there is great potential for defining road segments in a more comprehensive way by merging the three definitions.

### B. Homogeneous Segmentation Methods

The primary objective of homogeneous segmentation is to derive road segments where observations tend to be homogeneous, similar, or approximate. Most studies utilize homogeneous segmentation methods in road deterioration data analysis. The coefficient of variation (CV)-based method and the CDA are two typical homogeneous segmentation methods.

The CV is a fundamental statistical indicator for measuring the closeness of a group of data [31]–[33]. It is computed as the ratio between the standard deviation and mean value. The MCV method aims at identifying road segments with the minimum CV. The MCV and relevant methods have been widely used in signal processing [34], image classification and reconstruction [33], [35], [36], and system reliability analysis [37]. The major advantage of the MCV method is that it can effectively detect data groups with high homogeneity.

The CDA segments road data by detecting locations of change points using a cumulative area function and its slope function [38]–[40]. In addition to road data, the CDA has also been applied in the segmentation and classification of images [41]. In general, the CDA includes three steps. First, a cumulative area function is constructed with observations along a road. Then, the cumulative difference between the cumulative area function and cumulative mean values is computed to reveal observation variations. Finally, the change point locations are determined as the algebraic sign changes of the slope of the cumulative difference function. In practice, owing to the sensitivity of the CDA to suddenly changed observations and outliers, the CDA requires modifications with data smoothing, removing outliers, setting a minimum segment length, and setting iterations [42]. The modification steps are selected based on observations and practical requirements.

## III. Material and Methods

### A. Study Area and Data

The road network in the Mid West Gascoyne region is a critical exemplar for Australian road infrastructure systems, and for the world-wide spatial statistical analysis of road infrastructure performance. The first factor in its importance relates to essential locations and the diverse and comprehensive functions of roads. Fig. 1 shows that the road network links in Perth, the capital city of Western Australia (WA), which includes a densely distributed population, major ports, outer grain production areas, and remote mining regions. Thus,

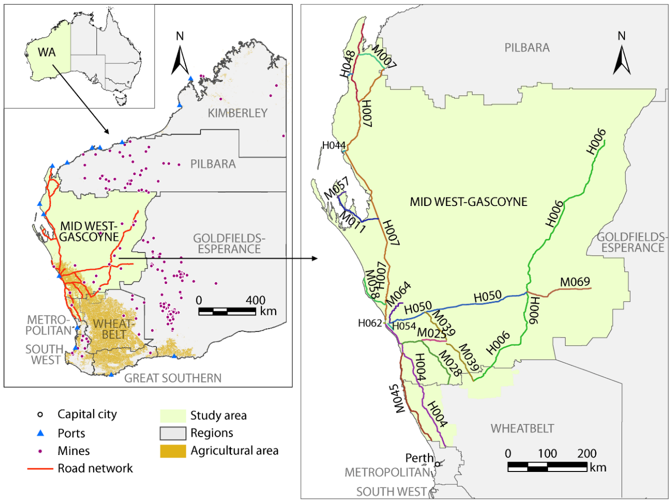


Fig. 1. Location and distribution of road network in the Mid West Gascoyne region in Western Australia, Australia.

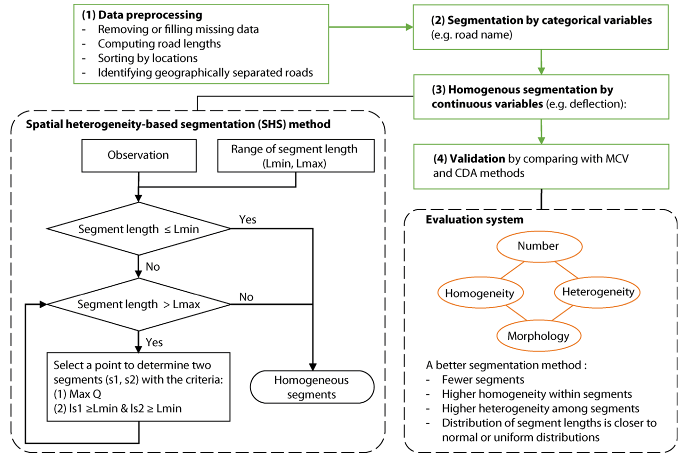


Fig. 2. Steps of spatial network data segmentation, flow chart of the spatial heterogeneity-based segmentation (SHS) method, and the evaluation system for comparing homogeneous segmentation methods, including cumulative difference approach (CDA) and the minimization coefficient of variation (MCV).

the road network covers both urban passenger transport and heavy vehicle freight transportation, such as port logistics and mining and agricultural supply chains.

In addition, this road network is typical for evaluation of "Traffic Speed Deflectometer" (TSD)-based road deterioration data in Australia. The TSD is a heavy vehicle-based road deterioration monitoring system consisting of Doppler lasers, 3D sensors, GPS, cameras, and temperature probes [43]. Table I lists a summary of the road deterioration data collected by the TSD system in this study. In total, 364,901 observations of road deteriorations within an interval of 10 m are collected on 19 highways with a total length of 3649.01 km in the Mid West Gascoyne road network. The Great Northern Highway (H006) and the North West Coastal Highway (H007) are the two longest roads, and their lengths account for 40% of the entire road network length. Road deterioration variables include curvature and deflection. Curvature presents asphalt fatigue with a shape variation of the pavement surface under certain loads. Deflection indicates the pavement strength, and is monitored as the maximum depression of a pavement surface under a standard load. Curvature can be computed as the maximum deflection for a load position minus the deflection at this position when the load is 200 mm away. The mean curvature and deflection of the road network are 152.79 $\mu$m and 341.34 $\mu$m, respectively. In general, when the curvature is higher than 300 $\mu$m or the deflection is higher than 700 $\mu$m, the road surface conditions are poor, and maintenance and reconstruction are required. In the study, 6.3% and 5.1% of the road lengths are above the high-risk thresholds for curvature and deflection, respectively.

## *B. Methods*

This study develops a SHS-based homogeneous segmentation model for road deterioration network data analysis and multi-scale road infrastructure system management. Meanwhile, an evaluation system is proposed to compare the effectiveness of different homogeneous segmentation methods. The methods in this study include four steps (Fig. 2): data pre-processing, segmentation by categorical variables, homogeneous segmentation by continuous variables, and model validation. The steps are introduced in the following subsections.

*1) Data Pre-Processing and Spatial Analysis:* The aim of data pre-processing is to ensure that the road deterioration network data is organized in a logical way. The data pre-processing includes four parts. The first part is to remove or fill missing data. Missing data is common in raw sensor monitoring data. In this study, curvature and deflection are monitored at a 10 m interval using an updated TSD system across the network, without missing data. The second part is computing road lengths of observations. Each observation represents 10 m of road surface conditions in the study. Third, the spatial locations of observations should be sorted to be along roads. Finally, geographically separated roads with identical road numbers and names should be identified and regarded as two roads.

To further explore the spatial variations of road deteriorations, a one-dimensional spatial variogram is estimated for deterioration data along the spatial line of each road. The coefficients of the variograms are fitted using weighted least squares functions from the R "gstat" package, which can perform multivariate geostatistical modeling [44]. The fitted coefficients of the variograms are then summarized using a road length-weighted mean approach, to describe the general scales of the spatial variations of the spatial line-based curvature and deflection.

*2) Road Segmentation by Variables:* In this study, road segments are determined by both categorical and continuous variables, as consistent with practical needs in road construction projects and network management. In this study, the categorical variables for homogeneous segmentation include road number and name. Optionally, categorical variables can also include carriage way (left road, right road, or single road), administrative region, pavement surfacing type, etc.

TABLE I
A SUMMARY OF ROAD DETERIORATION OBSERVATIONS DATA

| Road No | Road name | Length (km) | Curvature (μm) | | | Deflection (μm) | | |
|---|---|---|---|---|---|---|---|---|
| | | | min | max | mean | min | max | mean |
| H004 | Brand Highway | 364.76 | 1.13 | 568.78 | 176.56 | 32.04 | 1363.82 | 396.68 |
| H006 | Great Northern Highway | 752.60 | 2.59 | 658.68 | 147.49 | 23.13 | 1504.13 | 344.81 |
| H007 | North West Coastal Highway | 707.44 | 3.59 | 1081.34 | 168.01 | 16.34 | 1956.69 | 364.15 |
| H044 | Carnarvon Road | 5.00 | 38.48 | 709.68 | 304.88 | 213.92 | 1739.04 | 782.31 |
| H048 | Minilya Exmouth Road | 209.99 | 6.37 | 682.91 | 155.67 | 34.79 | 1345.64 | 321.95 |
| H050 | Geraldton-Mount Magnet Road | 322.51 | 2.05 | 623.04 | 134.53 | 15.89 | 1597.79 | 298.28 |
| H062 | John Willcock Link | 3.84 | 44.20 | 246.00 | 130.83 | 132.52 | 627.57 | 332.39 |
| M007 | Burkett Road | 78.26 | 13.53 | 544.40 | 135.09 | 65.16 | 1017.12 | 310.53 |
| M011 | Shark Bay Road | 125.69 | 5.83 | 459.51 | 102.98 | 18.19 | 956.85 | 224.40 |
| M025 | Mingenew-Morawa Road | 58.50 | 2.67 | 564.65 | 184.69 | 73.35 | 3965.42 | 439.85 |
| M028 | Midlands Road | 181.95 | 16.64 | 795.11 | 183.42 | 83.06 | 1780.42 | 444.72 |
| M039 | Wubin-Mullewa | 205.12 | 6.53 | 601.79 | 137.55 | 16.38 | 1449.75 | 327.92 |
| M045 | Indian Ocean Drive | 254.96 | 9.82 | 674.99 | 150.62 | 29.08 | 1270.60 | 304.18 |
| M047 | Coral Bay Road | 12.32 | 14.05 | 246.14 | 79.59 | 24.79 | 395.97 | 155.13 |
| M054 | Geraldton Walkaway Road | 20.12 | 26.52 | 535.15 | 179.50 | 47.22 | 1207.91 | 385.62 |
| M057 | Monkey Mia Road | 24.75 | 8.88 | 405.51 | 71.30 | 28.79 | 740.58 | 172.80 |
| M058 | Northampton-Kalbarri | 96.04 | 4.97 | 983.08 | 124.74 | 17.24 | 1739.31 | 293.02 |
| M064 | Moonyoonooka-Yuna Road | 71.22 | 8.84 | 651.58 | 173.72 | 41.07 | 1550.26 | 402.76 |
| M069 | Mount Magnet-Leinster | 153.94 | 14.29 | 626.16 | 130.81 | 28.75 | 1329.07 | 259.89 |
| | All roads | 3649.01 | 1.13 | 1081.34 | 152.79 | 15.89 | 3965.42 | 341.34 |

The continuous variables include the curvature and deflection sensor monitoring data.

*3) Spatial Heterogeneity-Based Segmentation (SHS) Model:* The SHS model is developed by integrating the homogeneous segmentation of network data and a spatial stratified heterogeneity analysis. The computation of the SHS model includes two steps. The first step is to compare the length of a spatial line segment data with the required threshold of road segment length. If the length of the spatial line segment data is shorter than the required minimum segment length, the data is regarded as a segment. If the length of the data is longer than the required maximum segment length, the data should be segmented using the segmentation approach described in the second step. In this study, three segment length thresholds are set for the multi-scale road infrastructure system: 100–500 m for project-level segmentation, and 1–5 km and 10–50 km for network-level segmentation.

The second step is to divide the data into two segments by selecting a change point that meets two criteria: the data between the two segments has the highest spatial heterogeneity, and the lengths of both segments are within the required threshold for segment length. The heterogeneity ($Q_s$) of the data in the two segments is quantified using a factor detector model from the spatial stratified heterogeneity method [45], [46]:

$$Q_s = 1 - \frac{N_a \sigma_a^2 + N_b \sigma_b^2}{N_\sigma^2} \tag{1}$$

where $N_i (i = a \ or \ i = b)$ and $\sigma_i$ are the number and standard deviation of the observations of the segment $a$ or segment $b$, respectively, and $N$ and $\sigma$ are the number and standard deviation of all observations, respectively. The spatial stratified heterogeneity is widely used for evaluating spatial heterogeneity among strata defined by spatial explanatory variables [24]–[26]. In this study, it is applied for quantifying the heterogeneity of the segment-based data. If the segmented data are longer than required maximum segment length, the segmentation process will be repeated until all segment lengths are within the required length threshold. If two or more continuous variables are used in the homogenous segmentation, a mean $Q_s$ value of the multiple variables is computed during each iteration.

*4) Segmentation Method Evaluation System for Spatial Line Data:* This study proposes a segmentation method evaluation system for spatial line data. The evaluation system examines four aspects: the number of segments, homogeneity within segments, heterogeneity among segments, and morphological characteristics of segments. First, the number of segments indicates the effectiveness of the methods in segmenting spatial line data. From this aspect, fewer segments means the method can more effectively segment the line data as compared with other methods.

Second, the homogeneity of the data within segments reveals whether the data within segments tends to be similar and has a uniform data structure. In this study, the homogeneity within segments is computed as:

$$H = \frac{1}{\sum_i c_i} \cdot \frac{N}{100} \tag{2}$$

where $N$ is the number of observations, $c_i (i = 1, \ldots, s)$ is the CV of segment $i$, and $s$ is the number of segments. The CV is the standard deviation divided by the mean value [47]. A higher value of the homogeneity within segments means that observations within the segments are more similar, and have a more uniform data structure. In practice, the percentage of lengths of road segments with CV values lower than 0.25 ($\boldsymbol{p}_{0.25}$) is generally used to indicate the effectiveness of segmentation methods.

Third, the heterogeneity among segments highlights the spatial disparities of data among different segments. It is quantified using a factor detector model of the spatial stratified

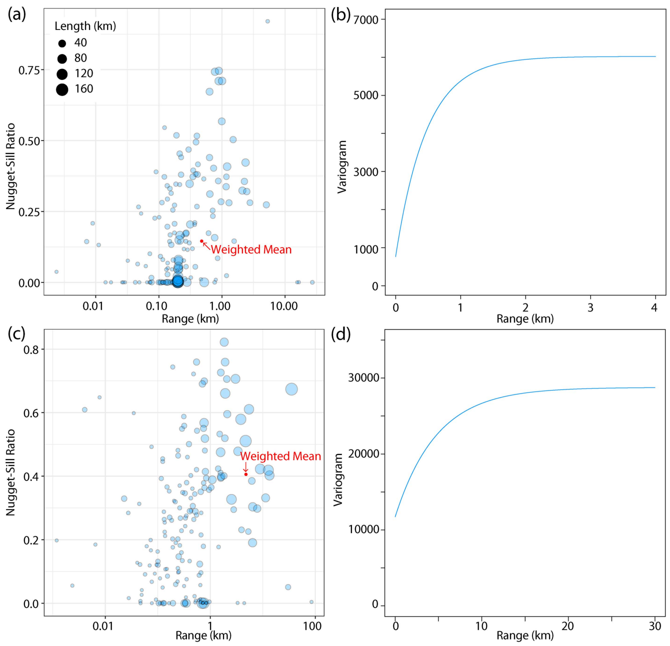


Fig. 3. Variogram coefficients and lines modeled with one-dimensional spatial variograms for road-based curvature (a and b) and deflection (c and d).

heterogeneity method:

$$Q = 1 - \frac{\sum_{i=1}^{s} N_i \sigma_i^2}{N\sigma^2} \quad (3)$$

where $N_i$ and $\sigma_i$ are the number and standard deviation of the observations of segment $i$, respectively, and $\sigma$ is the standard deviation of all observations.

Finally, the morphological characteristics of segments are computed using morphological indicators, to identify the distribution patterns of segment lengths. The segment length distribution is compared with two common statistical distributions, the normal distribution and uniform distribution. The closeness between the segment length distribution and one of the statistical distributions is calculated using the chi square test [48], [49], where the chi square statistical value is used to assess the relative closeness derived from different segmentation methods. A lower value of the chi square statistic indicates a higher relative closeness.

## IV. Results

### *A. Statistics and Geostatistics of Road Deteriorations Network Data*

The road deterioration network data, including curvature and deflection, are pre-processed for the following analysis and homogenous segmentation. In total, 219 parts of roads are identified on 19 highways. The minimum, mean, and maximum lengths of the road parts are 0.11 km, 16.66 km, and 170.45 km, respectively. For reliable geostatistical analysis, deterioration data are selected for spatial variograms estimation from 184 (84.02%) roads where the numbers of observations are higher than 50. The sum of the lengths of the selected roads accounts for 96.96% of all roads. In this study, exponential models are fitted to deterioration variograms. The coefficients of the variograms include nugget, sill, and range. The nugget-sill ratio is calculated to reveal the unsolved variation at scales finer than the sensor-monitoring resolution of the deteriorations (10 m). A practical range is computed as the three times the range in the exponential model [50]. Fig. 3 shows the summary of the variogram coefficients for spatial line-based curvature and deflection, and corresponding variogram lines fitted with road length-weighted mean coefficients of the variograms. The weighted estimated coefficients of the deterioration variogram lines are summarized in Table II. The nugget-sill ratios of the curvature on 62.35% of the roads are lower than 20%, and the nugget-sill ratios of deflection on 44.02% of the roads are lower than 20%. The road length-weighted mean nugget-sill ratios of curvature and deflection are 14.54% and 40.77%, respectively. Thus, the current sensor monitoring resolution can satisfy the requirements for accurate analysis of deteriorations, especially for curvature analysis. The practical ranges of the spatial variations of curvature and deflection are 1.43 km and 14.33 km, respectively. The relatively short correlation distance of the curvature distribution and the long correlation distance of the deflection distribution indicate that curvature and deflection have distinct spatial structures.

TABLE II
Road Length-Weighted Coefficients of Deterioration Variograms

| Parameters | Curvature | Deflection |
|---|---|---|
| Nugget | 736.83 | 11730.25 |
| Sill | 6028.56 | 28769.91 |
| Nugget-sill ratio | 14.54% | 40.77% |
| Range (km) | 0.477 | 4.778 |
| Practical range (km) | 1.431 | 14.334 |
| Road numbers (% of all roads) | 184 (84.02%) | 184 (84.02%) |
| Road lengths (km) (% of all roads) | 3537.95 (96.96%) | 3537.95 (96.96%) |

### *B. SHS-Based Segmentations*

Road deterioration maps (Fig. 4) demonstrate both the project- and network-level segment-based curvature and deflection distributions identified by the SHS approach. According to practices of road construction projects and decision-making experience of road network management and road maintenance strategies in WA, the project-level segments range from 100 m to 500 m, and the network-level segments range from 1 km to 5 km and from 10 km to 50 km. For instance, a majority of road construction projects deal with roads of a few hundred meters, such as maintenance for various types of local defects, so the project-level segments are defined as 100 - 500 m. When longer roads are damaged and need to be resurfaced, they will be regarded as network-level segments ranging from 1 to 5 km in the study. Then, resurfacing or rehabilitation activities may be required for road maintenance. For road authority, such Main Roads WA, continuous and regular road construction and maintenance plans are proposed from the perspective of the whole network management. Therefore,

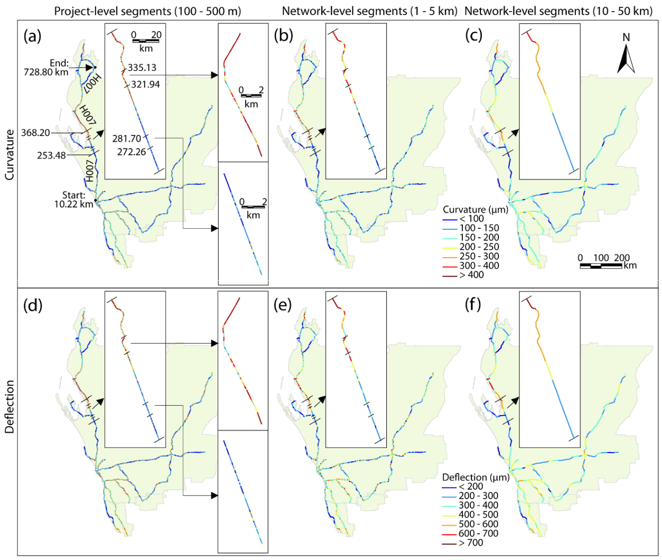


Fig. 4. Spatial distributions of project- and network-level segments across the network. Curvature: (a) project-level, (b) network-level (1–5 km), and (c) network-level (10–50 km). Deflection: (d) project-level, (e) network-level (1–5 km), and (f) network-level (10–50 km).

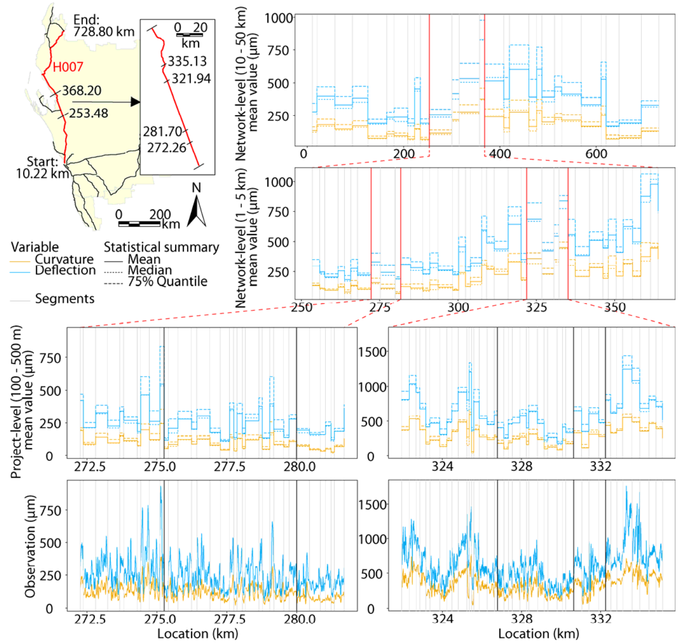


Fig. 5. Statistical comparison of project- and network-level segments derived by the SHS method.

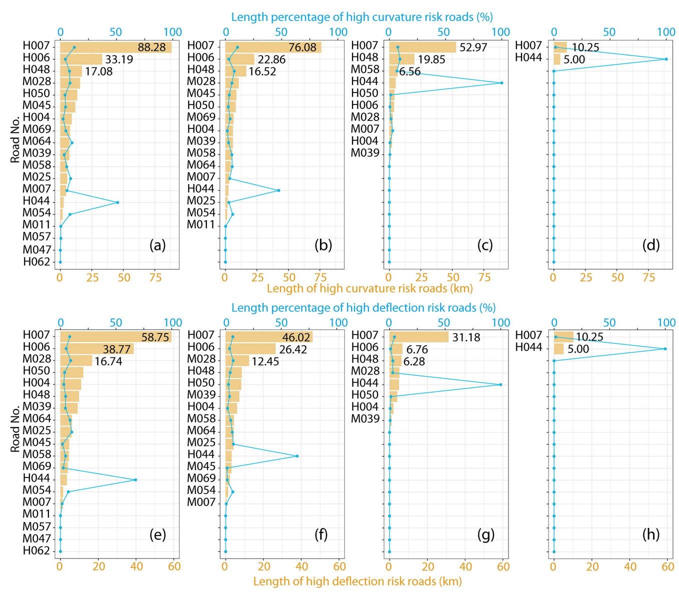


Fig. 6. Comparison of high deterioration risk roads. High-curvature-risk roads: (a) observations, (b) project-level segments, (c) network-level (1–5 km) segments, and (d) network-level (10–50 km) segments. High-deflection-risk roads: (e) observations, (f) project-level segments, (g) network-level (1–5 km) segments, and (h) network-level (10–50 km) segments.

10 - 50 km road segments are applicable for effective road construction design and maintenance strategies.

By using the sensor monitoring deterioration data, the SHS model identifies 12,594 project-level segments, 1,271 network-level (1–5 km) segments, and 134 network-level (10–50 km) segments. The deterioration values within segments are summarized using mean values to present spatial scale effects on maps. Three parts of the segment-based deterioration data selected from the North West Coastal Highway (H007) are used as examples for the comparison of project- and network-level homogenous segmentations. The first example is the segment-based data from 253.48 km to 368.20 km, where deteriorations in the northern part are relatively higher than in the southern part. The other two examples are segment-based data from 321.94 km to 335.13 km, where deteriorations are generally high, and segment-based data from 272.26 km to 281.70 km, where deteriorations are relatively low. The segment-based deteriorations on the three examples and the entire road network indicate that the project-level segments can effectively summarize deterioration observations, and can be widely used for local construction and road maintenance projects. The network-level segments are a summary of project-level segment data. They are essential for regional construction and maintenance allocation and road network asset management.

In addition, the observed and segment-based deterioration data on the example roads are visualized with statistical summaries (Fig. 5). The statistical summaries of the segment-based data include mean, median, and 75% quantile values, where the 75% quantile values reveal patterns of relatively high deteriorations within segments. The visualization demonstrates that the SHS model can effectively segment road data while ensuring high homogeneity of data within segments, and high heterogeneity of data among different segments.

Finally, the distributions of roads with a high deterioration risk identified at the project and network levels are compared for curvature and deflection (Fig. 6). In general, if the road surface curvature is higher than 300 $\mu$m or the deflection is higher than 700 $\mu$m, the road is in poor condition, and requires extensive maintenance activities, and perhaps even reconstruction. In the study, both the sensor monitoring observations and the segment-based data are compared with the high deterioration risk thresholds to identify high-risk roads.

TABLE III
SUMMARY OF HIGH DETERIORATION RISK ROADS OF THE NETWORK

| Deterioration risk | Observation/ Segments | Length (km) | Length percentage (%) | Segment number | Segment percentage (%) |
|---|---|---|---|---|---|
| High curvature risk | Observation | 230.78 | 6.32 | / | / |
| | Project-level (100–500 m) | 179.46 | 4.92 | 656 | 5.21 |
| | Network-level (1–5 km) | 100.23 | 2.75 | 36 | 2.83 |
| | Network-level (10–50 km) | 15.25 | 0.42 | 2 | 1.49 |
| High deflection risk | Observation | 187.09 | 5.13 | / | / |
| | Project-level (100–500 m) | 137.73 | 3.77 | 507 | 4.03 |
| | Network-level (1–5 km) | 61.58 | 1.69 | 23 | 1.81 |
| | Network-level (10–50 km) | 15.25 | 0.42 | 2 | 1.49 |

The high deterioration risk roads across the whole network are summarized in Table III. The comparison of high deterioration risk roads reveals three aspects. First, high-curvature-risk roads are longer than high-deflection-risk roads. Second, the spatial patterns of project-level high-risk roads are consistent with high-risk observation patterns. The top three high-curvature-risk roads are the North West Coastal Highway (H007), Great Northern Highway (H006), and Minilya Exmouth Road (H048), and the top three high-deflection-risk roads are the North West Coastal Highway, Great Northern Highway, and Midlands Roads (M028). In total, 76.08 km of high-curvature-risk roads and 46.02 km of high-deflection-risk roads are distributed in the North West Coastal Highway. Third, owing to the coarse resolution of network-level segments, the spatial patterns of network-level deteriorations are significantly different from project-level deterioration patterns. The North West Coastal Highway is still the road with the longest segments of high curvature and deflection risks, but the following high-risk roads are varied. In the network-level (1–5 km) results, in addition to the North West Coastal Highway, the length of the high-curvature-risk roads on the Minilya Exmouth Road reaches 19.85 km. The network-level (10–50 km) results also reveal that the entire Carnarvon Road (H044) is at high deterioration risk. The identification of roads above a high deterioration risk at different spatial scales can be flexibly used for practical road maintenance decision-making and construction projects.

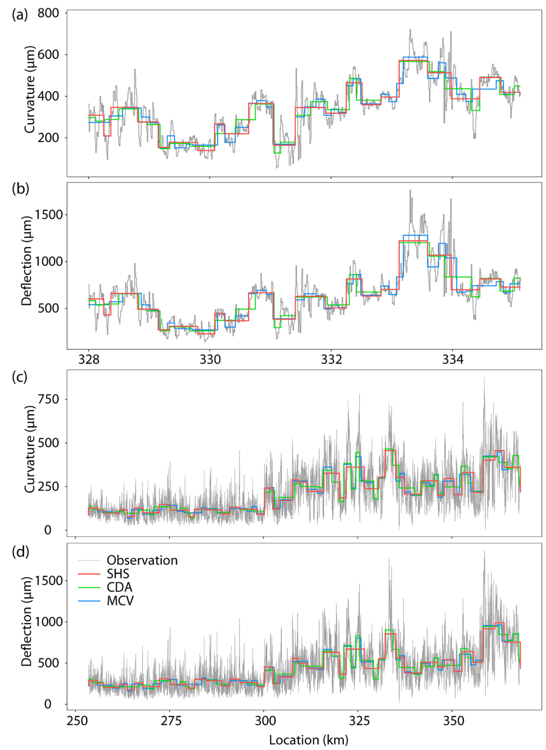


Fig. 7. Visualization comparison of three homogeneous segmentation methods: SHS, CDA, and MCV, for project-level (100–500 m) segments ((a) curvature segments, and (b) deflection) and network-level (1–5 km) segments ((c) curvature and (d) deflection) in parts of the road network.

## C. Model Validation

The effectiveness of the SHS model for road deterioration network data is comprehensively assessed in this study. Fig. 7 shows a visualization for comparison of the observations and segment-based data of the SHS, CDA, and MCV approaches. The results show that the SHS model has a stronger ability in grouping roads with similar deteriorations, and in differentiating neighbor roads with significant differences. To further quantitatively validate the performance of the homogeneous segmentation methods, this study proposes an evaluation system. The model performance is evaluated from four aspects: segment numbers, homogeneity within segments, heterogeneity among segments, and segment morphology. In the model validation, the SHS model is compared with the CDA and MCV approaches. The data are pre-processed with identical steps for the segmentations of the three models. The statistical evaluations of the three segmentation methods at both project and network levels are listed in Table IV. The statistical evaluations in regard to the four aspects are presented in the following paragraphs.

For the segment numbers, both the project- and network-level segmentations indicate that the SHS model can use the fewest number of segments to define the deterioration network data. The number of segments derived from CDA is less than that from the MCV approach. As compared with CDA, 11.4% and 22.4% of the numbers of segments can be reduced by the SHS model in the project- and network-level (1–5 km) segmentations, respectively. Thus, the segment number comparison demonstrates the effectiveness of the SHS model in segmentation.

The homogeneity of the data within segments is quantified using two indicators, the homogeneity index, and the percentage of the length of the road segment with CV values lower than 0.25 ( $p_{0.25}$ ). The statistical evaluation shows that

TABLE IV

STATISTICAL EVALUATION OF DIFFERENT SEGMENTATION METHODS AT PROJECT AND NETWORK LEVELS

| Segmentation level | Method | Number of segments | Homogeneity within segments | | Heterogeneity among segments | Morphology: difference to distributions | |
|---|---|---|---|---|---|---|---|
| | | | $H$ | $p_{0.25}$ | ($Q$) | Normal distribution | Uniform distribution |
| Project-level (100 - 500 m) | SHS | 12594 | 1.460 | 65.78% | 0.810 | 6426.18 | 1346.23 |
| | CDA | 14214 | 1.095 | 56.76% | 0.766 | 4181.81 | 2314.58 |
| | MCV | 18267 | 1.095 | 64.19% | 0.792 | 41260.26 | 55092.50 |
| Network-level (1 - 5 km) | SHS | 1271 | 8.393 | 17.61% | 0.549 | 268.75 | 55.01 |
| | CDA | 1637 | 6.568 | 17.55% | 0.523 | 1067.78 | 1181.23 |
| | MCV | 1670 | 6.568 | 18.36% | 0.526 | 1150.38 | 1279.48 |
| Network-level (10 - 50 km) | SHS | 134 | 62.763 | 1.89% | 0.338 | 47.44 | 28.21 |
| | CDA | 135 | 62.763 | 1.30% | 0.336 | 64.62 | 37.97 |
| | MCV | 136 | 62.398 | 1.85% | 0.337 | 52.42 | 38.63 |

1. The $p_{0.25}$ is the percentage of segment lengths with CV lower than 0.25
2. Morphological indicators are the comparisons between segment length distribution and two statistical distributions, normal distribution and uniform distribution
3. CDA: cumulative difference approach; MCV: minimization coefficient of variation

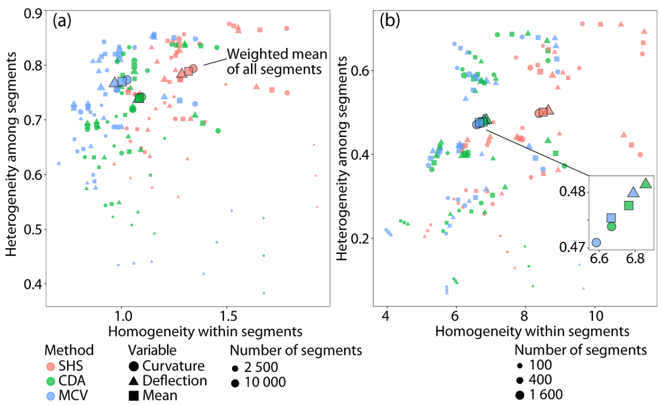


Fig. 8. Comparisons between heterogeneity among segments and homogeneity within segments for project-level (100–500 m) (a) and network-level (1–5 km) (b) results.

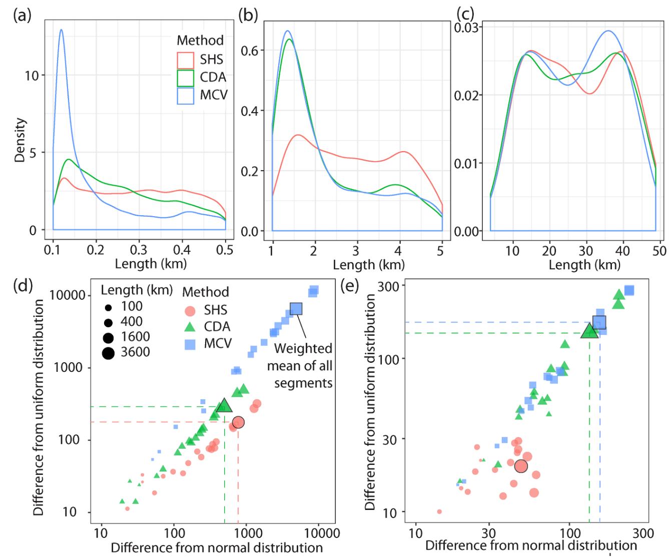


Fig. 9. Statistical distributions of segment lengths of SHS, CDA, and MCV methods at project-level (100–500 m) (a), network level (1–5 km) (b), and network-level (10–50 km) (c), and distributions of differences from normal and uniform distributions at project-level (100–500 m) (d) and network level (1–5 km) (e).

the project- and network-level results of the SHS model have the highest homogeneity within segments. In the project-level results, the CV values of 65.78% of the lengths of SHS-based road segments are lower than 0.25. The results of the SHS model have more segments with relatively low CV values as compared with the other two methods. In the network-level (1–5 km) results, the $\boldsymbol{p}_{0.25}$ values of the SHS-based segments are higher than those of the CDA-based results, indicating the relatively higher segmentation effectiveness of the SHS model.

The $\boldsymbol{p}_{0.25}$ values of the SHS-based segments are also lower than those of the MCV-based results, because the MCV-based results contain more segments, and especially more short roads with homogeneous values.

The heterogeneity of data among different segments across the network is quantified using a factor detector value. Both the project- and network-level results show that the SHS-based segments have the highest heterogeneity among segments. To further investigate the segmentation results, Fig. 8 compares the relationships among segment length, homogeneity within segments, and heterogeneity among segments at the project and network (1–5 km) levels. In general, data of relatively long segments have higher heterogeneity among segments than short segments, but the homogeneity within segments is not closely related to segment length. The road length weighted mean values reveal that the SHS-based segments have both the highest homogeneity within segments, and heterogeneity among segments for curvature, deflection, and the mean indicators as compared with the CDA and MCV approaches. In the project-level results, the CDA-based segments have higher homogeneity within segments than the MCV-based results, but they have lower heterogeneity among segments. In the network-level results, the indicators of the CDA-based segments at both dimensions are higher than the indicators of the MCV-based results.

Finally, the segment morphology is assessed, using the distribution pattern of segment length. The segment length distribution is compared with two common statistical distributions, the normal distribution and uniform distribution. The assumption is that if the experimental distribution is close to one of the two distributions, the segment length is normally distributed or uniformly distributed, instead of biased distributed. Fig. 9 shows the distribution patterns of the segment-based data identified by the SHS, CDA, and MCV methods, and their differences from normal and uniform distributions. In the project-level results, the length distribution of the SHS-based segments is closer to a uniform distribution, and that of the CDA-based segments is closer to a normal distribution. The lengths of the MCV-based segments are biased distributed. In the network-level (1–5 km) results, the length distributions of the three methods appear to be bimodal, with a main peak at approximately 1.5 km and a lower peak at approximately 4 km. The length distribution of the SHS-based segments is closer to a uniform distribution. Owing to the biased distributions of the CDA- and MCV-based segment lengths, the distribution of the SHS-based segment lengths is also closer to a normal distribution as compared with the results of other two methods. In the network-level results at 10–50 km, the distributions of the three methods are similar, and appear to be bimodal. However, the chi-square test indicates that the result of the SHS model is the best, and is closer to a uniform distribution. Therefore, the segment morphology evaluation indicates that results of the SHS model are generally closer to uniform distributions, and the distribution bias is much lower than that from the other two methods.

## V. Discussion

The proposed spatial heterogeneity-based homogeneous segmentation model is applied in multi-scale road infrastructure management and for investigating high deterioration risk roads across the network. The findings and explanations of the project- and network-level analysis are respectively presented in following paragraphs.

The project-level analysis aims at supporting the life cycle of road engineering, including the design of new roads, construction, operation, maintenance, and reconstruction. In the study, the spatial distribution patterns of deterioration data of project-level segments are consistent with the patterns from sensor monitoring observations. The consistent patterns indicate that the quantity of deterioration data is significantly reduced to 3.45% (12,594/ 364,901), and simultaneously, the key information of the deteriorations remains. For example, the high curvature and high-deflection-risk roads identified by the SHS model are approximately identical to the observed high-risk roads. In the study, the high deterioration risks mainly appear on the North West Coastal Highway, Great Northern Highway, Minilya Exmouth Road, and Midlands Road. Distance is a major factor in the freight transportation mode [51], meaning that roads near certain types of freight suppliers or needs may be responsible for more supply chains, and are associated with dense freight transportation and port, mining, and agricultural logistics. In addition, accurate project-level segments are critical for practical engineering works. One of the primary tasks of the project-level road infrastructure performance investigation is to optimize life-cycle solutions to satisfy stakeholders' requirements [52]. In general, the requirements consist of improving quality and productivity, reducing road user cost, real-time tracking of on-site construction progress, decreasing safety and environmental risks, and improving information management capabilities [53]–[55]. The project-level segments can significantly improve the accuracy and efficiency of decision making in the life cycle of road engineering, and can better satisfy users' requirements.

The network-level analysis is equally important as the project-level analysis, but they have different objectives and applications. First, the network-level analysis is desired for macro and large-spatial-scale decision making, instead of for single-construction projects. The network-level decision making includes statistics of road surface conditions across the network, strategic network investment for construction and maintenance, optimizing categories of deterioration risks, and network asset management. In addition, the spatial patterns of network-level deteriorations tend to be similar to project-level deterioration patterns, but they can present distinct regional information. In this study, the high-risk roads are varied at the project and network levels, owing to the different length percentages of high-risk observations within segments at the two levels. From the perspective of network-level management, extensive maintenance is required for roads where the overall deterioration is severe, or where most parts of the roads are in poor condition.

## VI. Conclusion

Defining road segments based on sensor monitoring and continuous deterioration data is a fundamental and critical issue for intelligent transportation systems, and smart and sustainable infrastructure systems. Homogeneous segmentation approaches provide effective solutions for investigating road deterioration network data. This study proposes a spatial heterogeneity-based homogeneous segmentation model for more effectively defining road segments using sensor data. In addition, an innovative model evaluation system is proposed in the study for comprehensive model validation. The primary advantage of the SHS model is that the optimal segment-based information can be identified with fewer segments. The optimal segment-based information includes a relatively high homogeneity of data within segments, and a high heterogeneity of data among different segments. Both the project- and network-level segmentation results indicate that the deterioration data within SHS-based segments tends to be approximately similar, and the data among neighbor SHS-based segments are significantly varied. Meanwhile, the SHS model can generate more uniformly distributed lengths of segments. The morphological characteristics of the SHS-based segments can significantly reduce the impacts of massive short segments on practical works and are identified to ensure higher segmentation effectiveness. As such, the SHS model and concepts and knowledge of the model evaluation system can be potentially utilized in broader research regarding network data segmentation and spatial model evaluations in transportation and road infrastructure. The multi-scale spatial analysis for segment-based road deteriorations can be flexibly utilized in various project- and network-level studies, construction, and road infrastructure management. Therefore, a data-driven road segment definition is not only essential for understanding and applying sensor monitoring big data, but is also practical for road construction works and network asset management.

## REFERENCES


[1] W. Wang, S. Yang, H. E. Stanley, and J. Gao, "Local floods induce large-scale abrupt failures of road networks," *Nature Commun.*, vol. 10, no. 1, p. 2114, Dec. 2019.

[2] S. M. Khan, M. Chowdhury, E. A. Morris, and L. Deka, "Synergizing roadway infrastructure investment with digital infrastructure for infrastructure-based connected vehicle applications: Review of current status and future directions," *J. Infrastruct. Syst.*, vol. 25, no. 4, Dec. 2019, Art. no. 03119001.

[3] A. Reggiani, P. Nijkamp, and D. Lanzi, "Transport resilience and vulnerability: The role of connectivity," *Transp. Res. Part A, Policy Pract.*, vol. 81, pp. 4–15, Nov. 2015.

[4] Y. Song *et al.*, "Spatial and temporal variations of spatial population accessibility to public hospitals: A case study of rural–urban comparison," *GISci. Remote Sens.*, vol. 55, no. 5, pp. 718–744, Sep. 2018, doi: 10.1080/15481603.2018.1446713.

[5] R. Bridgelall, "Precision bounds of pavement deterioration forecasts from connected vehicles," *J. Infrastruct. Syst.*, vol. 21, no. 1, Mar. 2015, Art. no. 04014033.

[6] C.-Y. Chu and P. L. Durango-Cohen, "Estimation of infrastructure performance models using state-space specifications of time series models," *Transp. Res. Part C, Emerg. Technol.*, vol. 15, no. 1, pp. 17–32, Feb. 2007.

[7] Y. Song, X. Wang, G. Wright, D. Thatcher, P. Wu, and P. Felix, "Traffic volume prediction with segment-based regression kriging and its implementation in assessing the impact of heavy vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 232–243, Jan. 2019.

[8] A. Setyawan, J. Nainggolan, and A. Budiarto, "Predicting the remaining service life of road using pavement condition index," *Proc. Eng.*, vol. 125, pp. 417–423, Nov. 2015.

[9] S. Werkmeister and D. Alabaster, "Estimation of remaining pavement life of low-volume roads with falling weight deflectometer results: A practical method," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1989, no. 1, pp. 261–269, Jan. 2007.

[10] D. S. Gedafa, M. Hossain, R. Miller, and T. Van, "Estimation of remaining service life of flexible pavements from surface deflections," *J. Transp. Eng.*, vol. 136, no. 4, pp. 342–352, Apr. 2010.

[11] Y. Song *et al.*, "Segment-based spatial analysis for assessing road infrastructure performance using monitoring observations and remote sensing data," *Remote Sens.*, vol. 10, no. 11, p. 1696, Oct. 2018.

[12] Z. Li, C. Cheng, M.-P. Kwan, X. Tong, and S. Tian, "Identifying asphalt pavement distress using UAV LiDAR point cloud data and random forest classification," *ISPRS Int. J. Geo-Inf.*, vol. 8, no. 1, p. 39, Jan. 2019.

[13] E. Schnebele, B. F. Tanyu, G. Cervone, and N. Waters, "Review of remote sensing methodologies for pavement management and assessment," *Eur. Transp. Res. Rev.*, vol. 7, no. 2, p. 7, Jun. 2015.

[14] K. Kobayashi and K. Kaito, "Big data-based deterioration prediction models and infrastructure management: Towards assetmetrics," *Struct. Infrastruct. Eng.*, vol. 13, no. 1, pp. 84–93, Jan. 2017.

[15] M. Romano, M. S. Siegel, and H. Y. Chan, "Creating a predictive model for pavement deterioration using geographic weighted regression," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2672, no. 40, pp. 166–175, Dec. 2018.

[16] S. Rose, B. S. Mathew, K. P. Isaac, and A. S. Abhaya, "Risk based probabilistic pavement deterioration prediction models for low volume roads," *Int. J. Pavement Eng.*, vol. 19, no. 1, pp. 88–97, Jan. 2018.

[17] A. Vargas-Sobrado, L. Rodríguez-Solano, J. Aguiar-Moya, H. Hernández-Vega, and L. Loría-Salazar, "Truck weights on municipal and national roads without weight enforcement," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2673, no. 2, pp. 275–284, Feb. 2019.

[18] A. I. Rifai, S. Handayani, and R. Al Rasyid, "Data mining applied for national road maintenance decision support system," in *Proc. MATEC Web Conf.* Les Ulis, France: EDP Sciences, vol. 195, 2018, Art. no. 04007.

[19] X. Espinet and J. Rozenberg, "Prioritization of climate change adaptation interventions in a road network combining spatial socio-economic data, network criticality analysis, and flood risk assessments," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2672, no. 2, pp. 44–53, Dec. 2018.

[20] S. Amin, U. Tamima, and L. E. Amador-Jiménez, "Optimal pavement management: Resilient roads in support of emergency response of cyclone affected coastal areas," *Transp. Res. Part A, Policy Pract.*, vol. 119, pp. 45–61, Jan. 2019.

[21] C. Burnett and T. Blaschke, "A multi-scale segmentation/object relationship modelling methodology for landscape analysis," *Ecol. Model.*, vol. 168, no. 3, pp. 233–249, Oct. 2003.

[22] A. Lamonaca, P. Corona, and A. Barbati, "Exploring forest structural complexity by multi-scale segmentation of VHR imagery," *Remote Sens. Environ.*, vol. 112, no. 6, pp. 2839–2849, Jun. 2008.

[23] J. Liu, M. Du, and Z. Mao, "Scale computation on high spatial resolution remotely sensed imagery multi-scale segmentation," *Int. J. Remote Sens.*, vol. 38, no. 18, pp. 5186–5214, Sep. 2017.

[24] H. Ju *et al.*, "Driving forces and their interactions of built-up land expansion based on the geographical detector–a case study of Beijing, China," *Int. J. Geographical Inf. Sci.*, vol. 30, no. 11, pp. 2188–2207, Nov. 2016.

[25] W. Peng, T. Kuang, and S. Tao, "Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, Western China," *J. Cleaner Prod.*, vol. 233, pp. 353–367, Oct. 2019.

[26] T. Yang, F. Sun, W. Liu, H. Wang, T. Wang, and C. Liu, "Using geo-detector to attribute spatio-temporal variation of pan evaporation across China in 1961–2001," *Int. J. Climatol.*, vol. 39, no. 5, pp. 2833–2840, Apr. 2019.

[27] J. Wang, X. Rui, X. Song, X. Tan, C. Wang, and V. Raghavan, "A novel approach for generating routable road maps from vehicle GPS traces," *Int. J. Geographical Inf. Sci.*, vol. 29, no. 1, pp. 69–91, Jan. 2015.

[28] Q. Cai, M. Abdel-Aty, J. Lee, L. Wang, and X. Wang, "Developing a grouped random parameters multivariate spatial model to explore zonal effects for segment and intersection crash modeling," *Analytic Meth. Accident Res.*, vol. 19, pp. 1–15, Sep. 2018.

[29] G. Fountas, P. C. Anastasopoulos, and F. L. Mannering, "Analysis of vehicle accident-injury severities: A comparison of segment- versus accident-based latent class ordered probit models with class-probability functions," *Analytic Meth. Accident Res.*, vol. 18, pp. 15–32, Jun. 2018.

[30] G. Dell'Acqua and F. Russo, "Road performance evaluation using geometric consistency and pavement distress data," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2203, no. 1, pp. 194–202, Jan. 2011.

[31] G. Murtaza, H. Ali, and N. Badshah, "A robust local model for segmentation based on coefficient of variation," *J. Inf. Commun. Technol*, vol. 5, no. 1, pp. 30–39, 2011.

[32] N. Badshah, K. Chen, H. Ali, and G. Murtaza, "Coefficient of variation based image selective segmentation model using active contours," *East Asian J. Appl. Math.*, vol. 2, no. 2, pp. 150–169, May 2012.

[33] X. Jiang, D. Zhang, H. Lin, X. Li, J. Xiao, and B. Li, "A robust image segmentation approach using fuzzy C-means clustering with local coefficient of variation," in *Recent Developments in Intelligent Computing, Communication and Devices*, vol. 752. Singapore: Springer, 2019, pp. 93–102.

[34] S. Durand and J. Froment, "Reconstruction of wavelet coefficients using total variation minimization," *SIAM J. Sci. Comput.*, vol. 24, no. 5, pp. 1754–1767, Jan. 2003.

[35] D. Needell and R. Ward, "Stable image reconstruction using total variation minimization," *SIAM J. Imag. Sci.*, vol. 6, no. 2, pp. 1035–1058, Jan. 2013.

[36] K. D. Paulsen and H. Jiang, "Enhanced frequency-domain optical image reconstruction in tissues through total-variation minimization," *Appl. Opt.*, vol. 35, no. 19, pp. 3447–3458, 1996.

[37] H. Tekiner-Mogulkoc and D. W. Coit, "System reliability optimization considering uncertainty: Minimization of the coefficient of variation for series-parallel systems," *IEEE Trans. Rel.*, vol. 60, no. 3, pp. 667–674, Sep. 2011.

[38] *AASHTO Guide for Design of Pavement Strcture. Appendix J: Analysis Unit Delineation by Cumulative Differences*, Amer. Assoc. State Highway Transp. Off., Washington, DC, USA, 1993.

[39] J. Kennedy, A. Shalaby, and R. Cauwenberghe, "Dynamic segmentation of pavement surface condition data," in *Proc. 3rd Transp. Speciality Conf. Can. Soc. Civil Eng.*, 2000, pp. 1–8.

[40] W. V. Ping, Z. Yang, L. Gan, and B. Dietrich, "Development of procedure for automated segmentation of pavement rut data," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1655, no. 1, pp. 65–73, Jan. 1999.

[41] Y. Zhang, J. Yang, K. Liu, and X. Zhang, "Self-detection of optical contamination or occlusion in vehicle vision systems," *Opt. Eng.*, vol. 47, no. 6, 2008, Art. no. 067006.

[42] S. Cafiso and A. Di Graziano, "Definition of homogenous sections in road pavement measurements," *Proc.-Social Behav. Sci.*, vol. 53, pp. 1069–1079, Oct. 2012.

[43] "An evaluation of the traffic speed deflectometer (TSD) for main roads Western Australia," ARRB Group, Main Roads Western Aust., Perth, WA, Australia, Tech. Rep. PSS16174-1, 2018.

[44] E. J. Pebesma, "Multivariable geostatistics in S: The gstat package," *Comput. Geosci.*, vol. 30, no. 7, pp. 683–691, Aug. 2004.

[45] J. Wang *et al.*, "Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China," *Int. J. Geographical Inf. Sci.*, vol. 24, no. 1, pp. 107–127, Jan. 2010.

[46] Y. Song, J. Wang, Y. Ge, and C. Xu, "An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: Cases with different types of spatial data," *GISci. Remote Sens.*, vol. 57, pp. 1–17, 2020, doi: 10.1080/15481603.2020.1760434.

[47] T. F. Fwa, S. A. Tan, C. T. Chuai, and Y. K. Guwe, "Expedient permeability measurement for porous pavement surface," *Int. J. Pavement Eng.*, vol. 2, no. 4, pp. 259–270, Dec. 2001.

[48] A. Satorra and P. M. Bentler, "A scaled difference chi-square test statistic for moment structure analysis," *Psychometrika*, vol. 66, no. 4, pp. 507–514, Dec. 2001.

[49] N. Mantel, "Chi-square tests with one degree of freedom; extensions of the Mantel-Haenszel procedure," *J. Amer. Stat. Assoc.*, vol. 58, no. 303, pp. 690–700, 1963.

[50] H. Wackernagel, *Multivariate Geostatistics: An Introduction With Applications*. Berlin, Germany: Springer, 2013, p. 41.

[51] B. Zgonc, M. Tekavčič, and M. Jakšič, "The impact of distance on mode choice in freight transport," *Eur. Transp. Res. Rev.*, vol. 11, no. 1, p. 10, Dec. 2019.

[52] J. Santos and A. Ferreira, "Life-cycle cost analysis system for pavement management at project level," *Int. J. Pavement Eng.*, vol. 14, no. 1, pp. 71–84, Jan. 2013.

[53] A. Ferreira and J. Santos, "Life-cycle cost analysis system for pavement management at project level: Sensitivity analysis to the discount rate," *Int. J. Pavement Eng.*, vol. 14, no. 7, pp. 655–673, Oct. 2013.

[54] G. Vadakpat, S. Stoffels, and K. Dixon, "Road user cost models for network-level pavement management," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1699, no. 1, pp. 49–57, Jan. 2000.

[55] J. B. Odoki, A. Di Graziano, and R. Akena, "A multi-criteria methodology for optimising road investments," *Proc. Inst. Civil Eng.-Transp.*, vol. 168, no. 1, pp. 34–47, 2015.

**Yongze Song** (Member, IEEE) received the B.S. and M.S. degrees in surveying and mapping from the China University of Geosciences, Beijing, China, in 2012 and 2015, respectively, and the Ph.D. degree in construction management from Curtin University, Perth, WA, Australia, in 2019.

He is currently a Research Fellow with Curtin University. His research interests include geographic information science, spatial statistics and modelling, and sustainable infrastructure.

He was a recipient of the Global Peer Review Awards by Publons, for being on the top 1% of peer reviewers in Geosciences and Cross-Field.

**Peng Wu** received the B.S. degree in project management from Tsinghua University, China, in 2006, the M.S. degree in construction management from Loughborough University, U.K., in 2007, and the Ph.D. degree in project management from the National University of Singapore, Singapore, in 2012.

He is currently a Professor with the Department of Construction Management, and an Associate Director with the Australasian Joint Research Centre for Building Information Modeling, Curtin University. His research areas include sustainable construction, lean production and construction, production and operations management, and life cycle assessment.

In 2016, he received the Discovery Early Career Research Award from the Australian Research Council, which is a prestigious award to support excellent basic and applied research by early career researchers.

**Daniel Gilmore** received the B.S. and M.P.E. (Civil) degrees from the University of Western Australia, Australia, in 2018.

He is currently working for Jacobs Engineering Group under the Asset Management Support Services contract for Main Roads Western Australia. In his final year of study, his thesis is the Optimization of Road Maintenance Scheduling Using Genetic Algorithms. His current works involve the application and improvement of asset management systems within the organization of Main Roads Western Australia. He is currently pursuing the integration of civil engineering practice within the asset management space.

He is a Recent Member of the Asset Management Council and Engineers Australia. He is invested in enhancing his career early to achieve Chartered Engineer status in Australia.

**Qindong Li** received the B.S. degree in civil engineering from Sichuan University, China, in 1992, and the M.E. degree in civil engineering from RMIT University, Australia, in 2003.

He has over 18 years' experience in design, construction and research of road transport infrastructures. He is currently the Asset Management Modeling and Analytics Manager of Main Roads Western Australia, Perth, WA, Australia. His research interests include pavement deterioration, whole of life costing, and the use of business intelligence in asset management.