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Robust interaction detector: A case of road life expectancy analysis

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A R T I C L E   I N F O

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A B S T R A C T

Spatial stratified heterogeneity, revealing the disparity mechanisms across spatial strata, can be effectively quantified using the geographical detector (GD). GD requires reasonable spatial discretization strategies to investigate the spatial association between the target variable and numerical independent variables. In previous studies, the Robust Geographical Detector (RGD) optimized spatial strata for examining the power of determinants (PD) of individual variables, which demonstrate more robust spatial discretization than other models. However, the GD's interaction detector that explores PD of the interaction of two variables still needs to be enhanced by the robust spatial discretization. This study develops a Robust Interaction Detector (RID), an improved interaction detector, using change detection algorithms for the robust spatial stratified heterogeneity analysis with multiple explanatory variables. RID is applied in a road life expectancy analysis in Western Australia. Results show that RID presents higher PD values than previous GD models, ensuring the growth of PD value with more spatial strata. The RID model indicates that the interactions between various transport variables and elevation are strongly associated with road life expectancy from the perspective of spatial patterns. The developed RID model provides significant potential for enhanced geospatial factor analysis across diverse fields.

Introduction

Spatial heterogeneity refers to the varying influence of geographical variables across space (Fotheringham et al., 1998). Spatial stratified heterogeneity (SSH), an essential kind of spatial heterogeneity, reveals the varying influence of variables by comparing the variation between spatial strata (Wang et al., 2010). Geographical detector (GD), consisting of factor, interaction, risk, and ecological detectors, is an effective method for assessing spatial association from the perspective of SSH. In GD, the factor detector explores the spatial association between the spatial dependent variable and independent variables based on the statistical variance of the dependent variable within strata, which is determined through the spatial discretization process for independent variables (Wang et al., 2016; Song et al., 2020a). The interaction detector of GD measures the spatial association between the dependent variable and the interaction of multiple variables, where the interaction is the spatial overlap of strata determined by categorical or discretized independent variables (Song and Wu, 2021).

Over a decade, GD and improved methods have been implemented in diverse research fields, such as urban planning (Feng et al., 2021), transport infrastructure (Song et al., 2020b), environmental science (Dasgupta et al., 2022), public health (Li et al., 2021), and climate change (Jiang et al., 2018). In most cases, independent variables for describing potential factors are usually continuous data,

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such as temperature, elevation, and population, which require reasonable spatial discretization prior to the GD modelling (Guo et al., 2022). Thus, discretization methods for continuous independent variables critically influence the performance of GD modelling, the power of determination (PD) values of potential variables, and the strength of spatial association (Cao et al., 2013).

Recently, several innovative methods broadened the GD model with the support of improved spatial discretization approaches. For instance, the optimal parameter-based geographical detector (OPGD) provides options for independent variable discretization based on the statistical distribution of variables, such as equal intervals, natural breaks, quantile, and geometric (Song et al., 2020a). In addition, the improved GD methods include the interactive detector for spatial association (IDSA) (Song et al., 2021), robust geographical detector (RGD) (Zhang et al., 2022), and geographically optimal zones-based heterogeneity (GOZH) (Luo et al., 2022) for spatial factor exploration, and generalized heterogeneity model (GHM) for spatial prediction (Luo et al., 2023). Among these methods, RGD employs a change point detection algorithm to effectively identify the robust and optimal spatial strata for individual variables (Zhang et al., 2022). RGD-derived robust spatial strata maximize spatial association between the dependent variable and independent variables with a given number of strata. Optimization algorithms are suitable for enhancing the factor detector, as the issue of discretizing independent variables can be converted into a single mathematical objective: minimizing the squared cost with given constraints (Page, 1955; Truong et al., 2020).

Despite the robustness and effectiveness of applying optimization algorithms on the factor detector, the research gap remains in exploring the robust spatial association between the dependent variable and the interaction of independent variables (Zhang et al., 2023). However, it is an essential challenge to optimize two targets at the same time. Optimization algorithms are suitable for the factor detector due to single criteria for one variable discretization, while it would be hard to apply optimizations on the discretization strategy with multiple research targets, i.e., identify optimal spatial strata for GD from two variables simultaneously.

This study develops a Robust Interaction Detector (RID) for identifying the robust spatial association between a dependent variable and the interaction of multiple independent variables. RID provides a new computing process for the interaction detector model that contains robust spatial discretization for the interaction of multiple variables. To achieve this objective, the robust spatial discretization identifies the discretization outcome that provides the highest PD value from all possible discretization options of variable interactions. RID is used to evaluate the interactions of variables affecting road seal life in rural regions of Western Australia. The effectiveness of RID is validated by the sensitivity of PD values to the number of discretization intervals and is compared to results from the OPGD models.

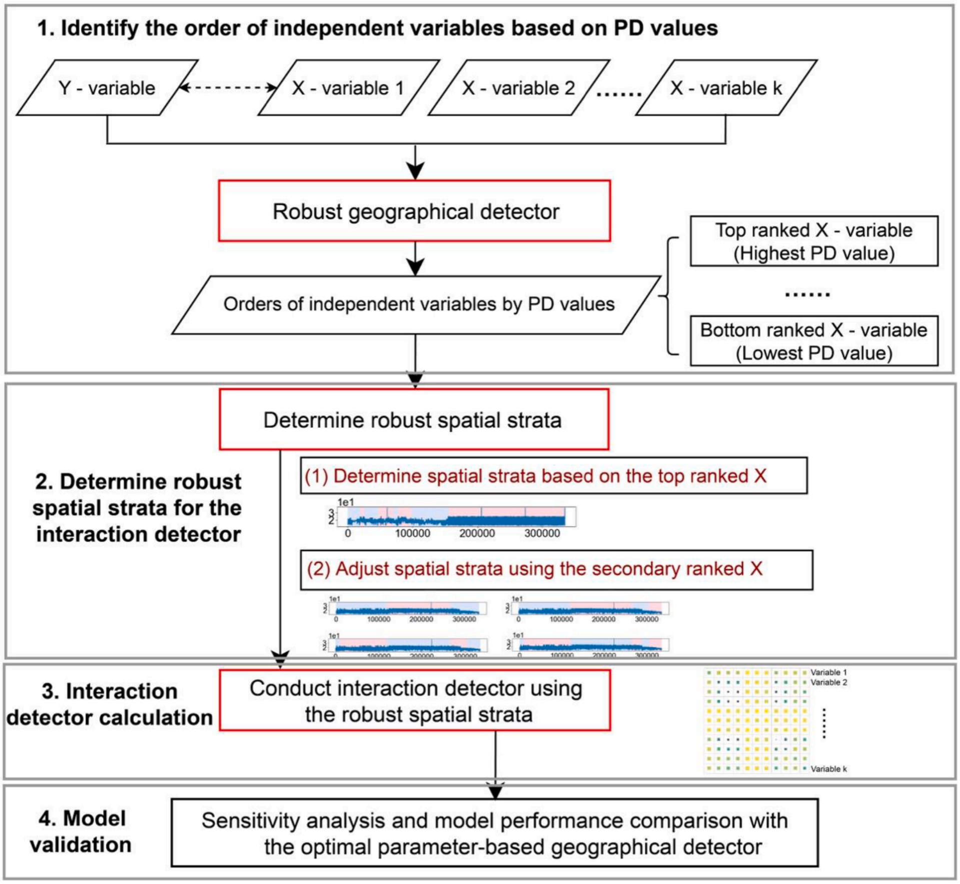

Fig. 1. Flowchart of the robust interaction detector (RID) for exploring robust spatial association.

Robust interaction detector

This study develops the RID for exploring the robust spatial association between a dependent variable and the spatial interaction of independent variables. RID enhances the interaction detector by using change point detection algorithms on multiple independent variables. Fig. 1 illustrates the steps of RID. On the one hand, RID is constructed based on the robust spatial strata derived from a robust spatial discretization process that aligns with the optimization algorithm in RGD (Zhang et al., 2023). On the other hand, the PD value of RID is computed using the identical approach of the GD model, as shown in Eq. (1) (Wang et al., 2010).

$$q = 1 - \frac{\sum_{h=1}^{k} N_h \delta_h^2}{N\delta^2} = 1 - \frac{SSW}{SST} \tag{1}$$

where N_h is the number of observations from the strata h by discretizing an independent variable; N is the number of observations within the whole study area; δ_h^2 is the variance of response variable value in the strata h; δ^2 is the variance of the response variable in the whole study area. In the interaction detector, the PD value is based on categorization or discretization from two variables. In RID, the discretization of two continuous variables is computed using a change point detection algorithm, given the effectiveness shown in RGD (Zhang et al., 2022). Details are presented in the following contents.

RID aims at maximizing the PD value of the interaction of two variables. A characteristic of the q-value in Eq. (1) is that an increase in the number of spatial strata generally generates a higher PD value, which is used in RID. The method first applies optimization algorithms to the independent variable that shows the strongest spatial associate as indicated by RGD. Then, the spatial strata are enhanced by adding more dividing points from the second variable. This strategy ensures that PD values from the interaction of variables are higher than those from single-factor detector results.

The first step of RID is to use RGD to identify the spatial association between the dependent variable and individual variables. The RGD results can provide the ranking of association strength between the dependent variable and independent variables. The ranking of spatial association is used to determine the order in which the optimization algorithms are applied to the independent variables when generating spatial strata of the interaction of variables.

The second step is to determine robust spatial strata for the interaction detector. The sensitivity analysis in previous studies has demonstrated that using the change point detection algorithm in RGD ensures the increase of PD value as the number of spatial strata increases. In RGD, it is recommended to use the robust spatial strata derived from the variable that has the highest PD value, meaning that the variable has the strongest spatial association with the dependent variable. Then, minor adjustments are made by adding more dividing points based on the second variable to the spatial strata determined by the first variable. Both the robust spatial strata from the first variable and the dividing points from the second variable can be generated from the RGD function and the change point detection process.

The third step is to validate the PD value of robust spatial strata from two selected variables on the interaction detector. In this study, the model is evaluated using the sensitivity analysis of assessing how PD values change with the increase of strata numbers and the model is compared to the OPGD model. For a fair comparison, the same settings of discretization numbers are used in both RID and OPGD. The OPGD model is conducted using the GD package in R programming (Song et al., 2020).

The general process of RID, together with RGD for individual variables, is shown below. The algorithms shown below also include the minimal number of observations in each spatial stratum as a parameter to ensure practical applications with large datasets. For case studies with a large number of observations, checking every possible combination can take a long time. Thus, setting a minimum strata size can speed up the search. The change point detection only checks at intervals that are multiples of this minimum size, providing a more efficient way to optimize the robust spatial discretization of the integer multiple of the minimal length and make a rough optimization on the series (Truong et al., 2020).

The process of robust interaction detector (RID)

```
function RGD (minimal length, specified number of spatial strata k, ranked y-variable series according to the x-variable)
    for all ranked sub-series with lengths no less than the minimal length do
        store all sub-series
    end for
    for all possible sub-series pairs constituting any length of a subset of y-series no less than the minimal length do
        record these sub-series pairs with the lowest costs and store them as C
    end for
    start searching for the changing points from the last observation (start point)
    while the required number of changing points are not all found do
        find two sub-series pairs with the lowest costs for the existing y-series from C
        record this changing point to the list L
        set the changing point as the next starting point
    end while
    categorize the sorted x-variable according to the list L, and save it as a dummy variable x-k
    factor detector(y-variable, x-k)
    return q-value, statistical significance
function RID (y-variable, all x-variables, range of spatial strata R)
    for all x-variables do
        for all values r in the range R do
```

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(*continued*)

The process of robust interaction detector (RID)
RGD (minimal length, number of stata *r*, *y*-variable ranked by *x*-variable)
end for
end for
sort the variable in descending order by RGD results
for all pairs of *x*-variables **do**
set the maximum available zone numbers for top-ranked variables; recall all dummy variables representing categorizations of *x*-variables
for all values *r* in the range *R* **do**
interaction detector(*y*-variable, top-ranked *x*-variable, lower-ranked *x*-variable in group ***r*)**
return *q*-value, statistical significance
Abbreviation: RID – Robust Interaction Detector; RGD – Robust Geographical Detector**.**

Case study: RID for rural road seal life analysis in Western Australia

Study area and research background

The RID is applied in a case study exploring variables affecting rural road seal life in Western Australia (WA). WA, the largest state in Australia, covers an area of 2.5 million square kilometers, and about 18,000 km of state roads. Main Roads Western Australia, the road authority of WA, conducted a year-long survey on the conditions and properties of the state roads across the state in 2020. The survey contains various aspects of roads, such as traffic volume, surface temperature, and pavement crack measures. These road variables are used for the estimation of rural road seal life and the analysis of its influencing factor. Statistics on the estimated rural road seal life and its influential factor analysis provide the road authority insights into the spatial pattern and the current conditions of the roads. Data analytic and modelling results can assist the local road authority with effective, strategic, and predictive infrastructure asset management. In this study, the focus is the road life expectancy of non-temporary seal roads in rural regions of WA.

Rural road seal life estimation and datasets of factors

The rural road seal life estimation is based on a model adopted by Austroads, an organization comprised of road authorities and agencies in Australia and New Zealand (Austroads, 2010). The road life expectancy, as shown in Eq. (2), is estimated based on air temperature, nominal size of seal, durability test results, and the risk factor.

$$Seal\ life = \left[\frac{0.158 * tMin - 0.107 * Risk + 0.84}{0.0498 * tAve - 0.0216 * Dura - 0.000381 * AggSize^2}\right]^2 \tag{2}$$

where ***tMin*** is the yearly mean of the daily minimum air temperature with a unit of degree Celsius; ***tAve*** is the average value of the yearly mean of the daily minimum and maximum air temperature with a unit of degree Celsius; ***Dura*** is the durability test results and taken as 10; ***AggSize*** is the nominal size of the seal with a unit of millimeter; Risk refers to the risk factor calculated by Eq. (3).

$$Risk = 0.00097 * Rain + 0.0064 * AADT^{0.5} + 0.00001 * Rain * AADT^{0.5} \tag{3}$$

where *Rain* is annual rainfall with a unit of millimeter; and *AADT* is the traffic volume on roads. The age of the road surface and pavement is also taken into consideration. Roads with a new seal added over the existing one within two years are expected to last an additional three years.

To support the state road authority in road asset management, factors' association with rural road seal life expectancy is explored. RID is applied to explore the spatial association between rural road life and potential influential road features, including their interactions. Potential factors influencing rural road life expectancy are listed in Table 1. The state road authority has measured various properties of roads and their cracking levels. Road properties include deflection and curvature from traffic speed deflectometer (TSD)

Table 1
Summary of variables associated with rural road seal life.

Category	Factor	Data source	Unit
Remote sensing data	Elevation - DEM	Google Earth Engine	m
	Urbanization - NTL		nanoWatts/cm2/sr
TSD data	Deflection	Main Roads Western Australia	μm
	Curvature		μm
Transport features	Legal road speed	Main Roads Western Australia	km/h
	Perc heavy		%
Road cracking measurements	Lane cracking	Main Roads Western Australia	–
	OWP cracking		–
	IWP cracking		–
	BWP cracking		–

data. Road speed limits (Legal speed) and the percentage of heavy vehicles (Perc heavy) are transport features on roads. Road cracks are measured at the lane (the entire road lane), outer wheel path (OWP), inner wheel path (IWP), and center wheel path (BWP). These road crack features are measures of cracks by the extent of transverse, longitudinal, or alligator. All road and crack properties are sampled at the 100-meter distance points alongside the roads. Furthermore, remote sensing data, including the digital elevation model (DEM) and nighttime light (NTL) from Google Earth Engine are utilized to indicate the feature of elevation and urbanization level on roads (Google Developers and Geoscience Australia, 2010). DEM is accessed from the Australian Smoothed Digital Elevation Model, and NTL is accessed from the VIIRS Stray Light Corrected Nighttime Day/Night Band Composites (Google Developers and Earth Observation Group, 2020).

Results

Rural road seal life in Western Australia

Fig. 2 shows the spatial distribution of estimated road seal life. Rural seal roads of the estimated road seal life vary from 12 years to 36 years, following a north-to-south geographical pattern. Rural seal roads in the northern part of the state have a shorter life expectancy, with a seal life of less than 17 years. In contrast, rural roads closer to the west coast of the state and those in the inner-south regions last longer. Their life expectancy can exceed 20 years, with some reaching up to 36 years.

Robust spatial strata on the interaction detector

The rank of value importance indicated by RGD

Fig. 3 shows the factors identified by RGD and affecting the estimated rural road seal life. The local road authority measures road features by undertaking surveys every 100-meter distance. Thus, the entire rural road network observations are composed of millions of data records. This research set the minimal observation of each spatial stratum as 1000 in the algorithm to optimize processing time. The number of spatial strata for each variable is set from 3 to 8. Transport features on roads, including legal road speed limits and the percentage of heavy vehicles, are the most significant factors influencing road life expectancy, followed by road elevation and road cracking features. The association between road seal life and road TSD features is low as shown by the near-zero PD values. Therefore, the impacts of individual variables demonstrate the importance of transport dynamics, heavy vehicle freight transportation, and geographical factors in road infrastructure maintenance and management.

Fig. 4 shows the details of the spatial association between rural road seal life and individual variables explored by RGD, i.e., the statistical distribution of rural road seal life grouped by each variable based on their robust spatial strata, set at eight distinct strata. The significant statistical variability in road seal life across the groups derived from road transport features also indicates their stronger association with rural road seal life expectancy than other features. Conversely, the uniform distribution of road life expectancy among statistical groups determined by deflection and curvature suggests a less statistical association between these features and road seal life expectancy.

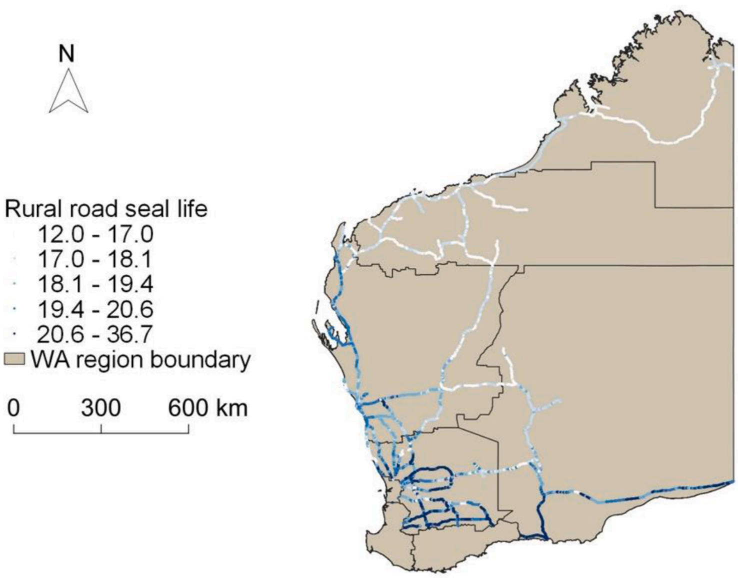

Fig. 2. Estimated rural road seal life in Western Australia.

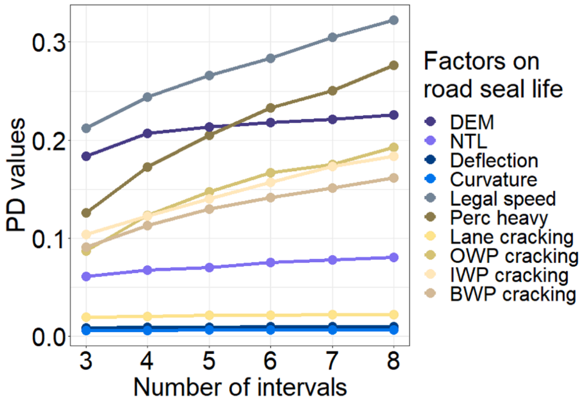

Fig. 3. Spatial association between rural road seal life and individual variables explored by robust geographical detector (RGD).

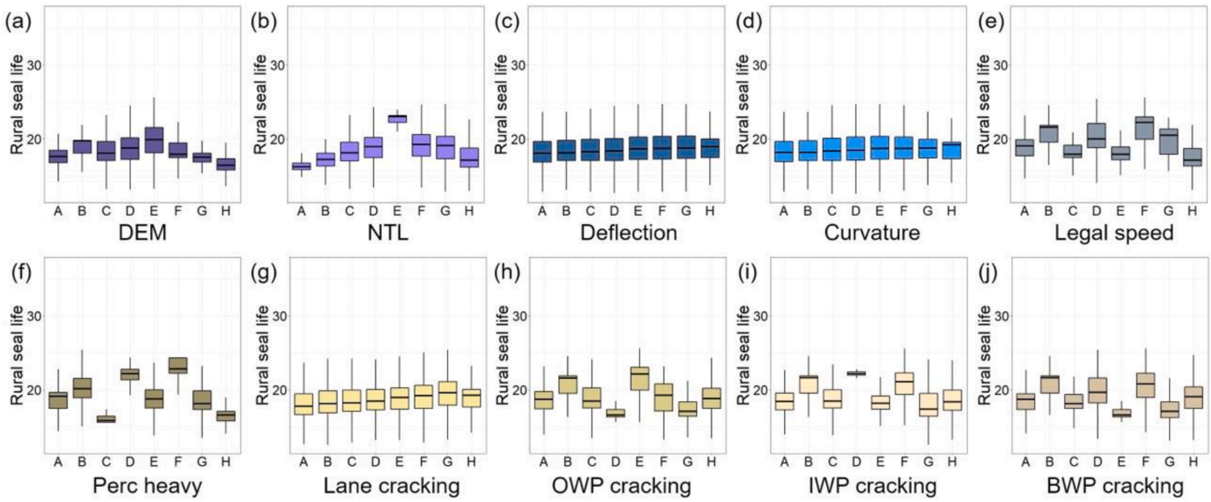

Fig. 4. Statistical distribution of rural road seal life grouped by robust spatial strata based on (a) DEM; (b) NTL; (c) Deflection; (d) Curvature; (e) Legal speed; (f) Perc heavy; (g) Lane cracking; (h) OWP cracking; (i) IWP cracking; and (j) BWP cracking.

Robust interaction detector

In this study, the RID is applied and validated to examine the influence of the spatial interaction among 10 variables on the estimated road seal life, as shown in Fig. 5. The number of spatial strata for each variable is set from 3 to 8. For each pair of variables, the first variable is set with the highest acceptable number of spatial strata derived from the robust spatial discretization of RGD. Then, the second variable adjusts the spatial strata by adding spatial strata (from 3 to 8) using the change point detection algorithm. The RID method indicates that the PD values of interactions of paired variables from the 10 selected variables range from 0.01 to 0.48. The interaction between the road speed limit and the percentage of heavy vehicles on roads is the most dominant interaction with a PD value of 0.48, followed by the interaction between the road speed limit and elevation with a PD value of 0.47. The heat plot shown in Fig. 5 indicates that the interactions involving transport features have a more significant impact compared to other combinations. This is due to higher single-factor association value from these two transport factors, and the properties of optimization algorithms for both RGD and RID in increasing PD values while adding more spatial strata. The detailed performance of the RID method is shown in the sensitivity analysis of model validation.

Model evaluation and comparison

This research evaluates RID through sensitivity analysis and compares it with the OPGD model. Fig. 6(a) shows the relationship between the growth of PD values and the addition of spatial strata for the second variable where the spatial strata of the first variable have been determined. The top five interactions of variables on rural road seal life demonstrate that the optimization algorithm guarantees a consistent increase in PD values as more spatial strata are added based on the second variable. As the performance of optimization on the factor detector evaluated in previous studies (Zhang et al., 2023), the optimization strategy also ensures the PD value growth with more spatial strata for individual variables. Thus, the change point detection algorithm can guarantee the growth of

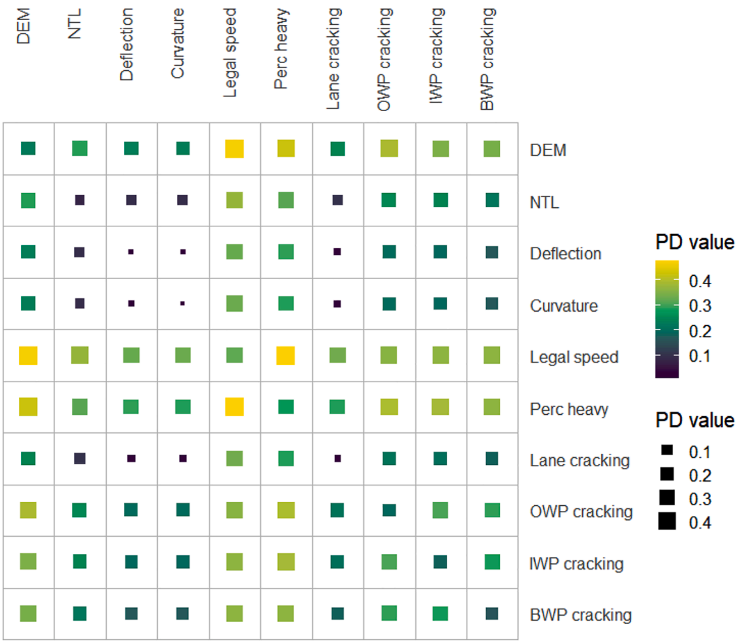

Fig. 5. The power of determinant (PD) values of the interaction of variables on rural road seal life examined by RID.

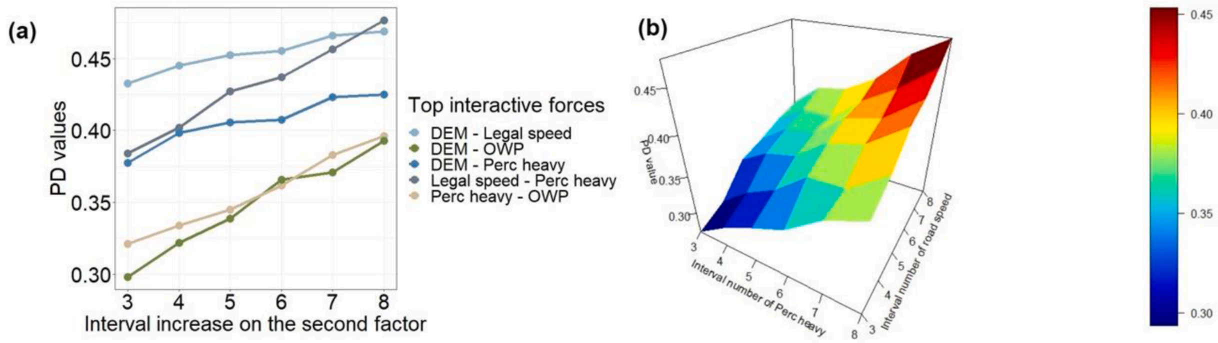

Fig. 6. Sensitivity analysis of robust interaction detector (RID) on the interactions with the top PD values. (a). Sensitivity analysis on top five interactions. (b) Sensitivity analysis on the interaction of speed limits and the percentage of heavy vehicles.

PD values for both single-factor association and multiple-factor interaction by adding spatial strata. Fig. 6(b) further demonstrates the PD value changes with the increase of interval numbers of both variables, given details of the interaction of two traffic variables, speed limits and the percentage of heavy vehicles. Results show that RID can ensure the consistent increase of PD values as the spatial strata increase for both variables, demonstrating the effectiveness and robustness of RID models.

In Fig. 7, we compare the results of RID and the interaction detector of the OPGD model. In the comparison, the OPGD model includes spatial discretization methods of 'equal', 'quantile', 'sd', 'natural', and 'geometric', and it sets the number of discretization intervals for both variables between 3 and 8, which is identical to the spatial strata numbers in RID. The OPGD returns the best PD results for each pair of factor interactions by comparing values with different sets of parameters. Fig. 7(a) visualizes the OPGD interaction detector results, with paired variable interactions showing PD values between 0.01 and 0.38. The OPGD results suggest that the interaction between the percentage of heavy vehicles and elevation has the strongest spatial association with rural road seal life. However, RID shows an enhanced outcome, where the PD value of the interaction between the percentage of heavy vehicles and elevation is 0.42. In fact, RID identifies at least five pairs of variable interactions with PD values higher than the OPGD's highest PD value of 0.38. OPGD indicates that interactions related to the percentage of heavy vehicles are more associated with rural road seal life than other interactions. However, RID shows that interactions related to both traffic variables, including the percentage of heavy vehicles and speed limits, are closely associated with rural road seal life. In addition, both RID and OPGD indicate that the interaction between road TSD features has the least association with road seal life.

Fig. 7(b) shows the improvements of RID compared with OPGD, quantified by the difference in PD values between RID and OPGD. By using RID, PD values increase for almost all variable interactions, except for the interaction between two TSD features. The

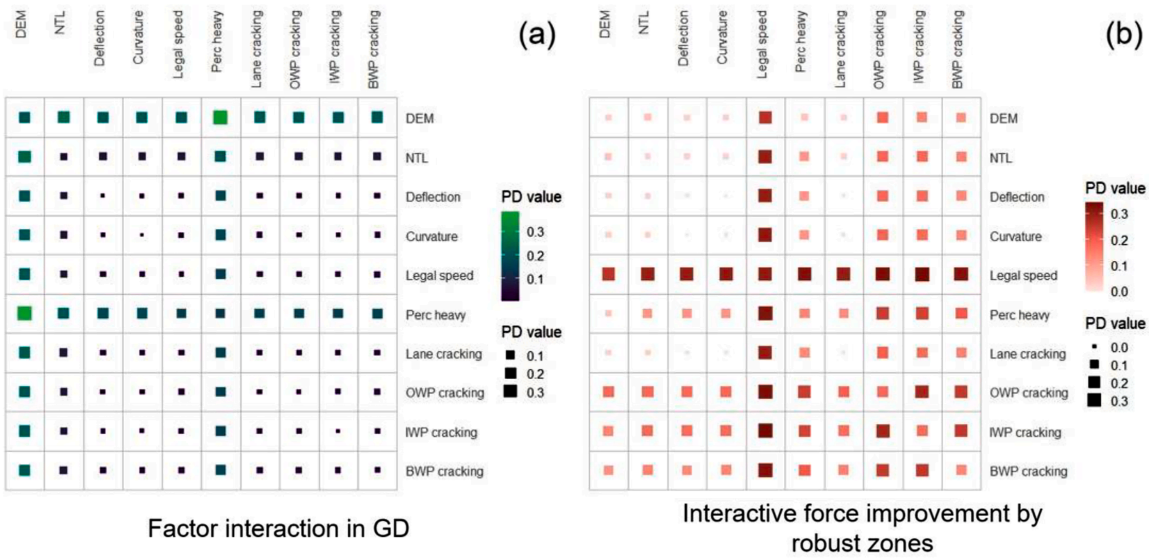

Fig. 7. Model comparison and improvement. (a). Factor interaction results in OPGD. (b). Improvements of interaction detector using robust spatial strata compared with OPGD.

interactions related to road speeds or cracking measures have essential improvements, with PD value increases ranging from 0.20 to 0.34.

Discussion

This study introduces an enhanced interaction detector model RID through the use of optimization algorithms. In this study, RID is implemented in examining potential variables related to rural road seal life in Western Australia revealing practical industry values. This study provides quantitative evidence for planning insights for local road authorities and presents an innovative approach to exploring variable interactions from a spatial heterogeneity perspective.

From a methodological perspective, this study develops a process to improve the performance of interaction detectors by using optimization algorithms. This enhancement leverages the change point detection algorithm for the factor detector of individual variables and the statistical properties of GD. This methodology design guarantees the maximum PD values for variable interactions among all variable interactions and the growth of PD value for the interaction detector as spatial strata increase, showing the robustness of the RID model. PID is particularly powerful in improving the effectiveness of interaction detector by involving variables with high PD values.

For practical industrial implications in road network planning and maintenance, this study first estimated state-wide rural road seal life in Western Australia based on the model proposed by Australian road authorities. Road seal life in the state has a distinct north-to-south spatial pattern. Rural roads in the southern part of Western Australia or close to the west coast have longer seal life, while roads in the inner northern areas may require more frequent maintenance efforts. This research found that the interaction of the percentage of heavy vehicles and road speeds had the highest spatial association with rural road seal life among all interactions. Meanwhile, variable interactions involving transport variables or elevation also show higher spatial association with rural road seal life as indicated by the RID model than other interactions.

We further provide a simulation study to test the performance of RID in detecting the association between interactive associations between linearly and non-linearly correlated variables. Full results are shown in the Appendix as an additional support of this model. In this simulation study, we prove that RID still outperforms OPGD in detecting variables' associations in general cases.

Conclusion

This study develops a Robust Interaction Detector (RID) model to evaluate robust spatial association by introducing an optimization approach for the robust spatial discretization of a pair of variables. The developed RID model is applied in assessing variables influencing rural road seal life, which demonstrates the effectiveness and robustness of RID in identifying explanatory variables and the practical industry benefits of RID-based analysis in infrastructure asset management. From the perspective of methodological perspective, RID provides higher and more robust PD values for spatial interaction from multiple variables compared with the interaction detector in OPGD. In addition, RID is reliable in quantifying the PD values since it guarantees the continuous increase of PD values as spatial strata increase. From the practical perspective, findings from the RID-based analysis show that strong spatial association between rural road seal life and the interaction involving transport and geographical variables. The RGD-based individual variable analysis and RID-based variable interaction analysis benefit the local road authorities with a better understanding of factors influencing rural road seal life expectancy and for developing future maintenance strategies. The developed RID model provides significant potential for advanced geospatial factor analysis across various fields.

Appendix: Further simulation test for RID – Detecting statistical interactions between linearly and non-linearly correlated factors

As a support of evidence, we further provide a simulation test for demonstrating the power of RID in detecting statistical associations between linearly and non-linearly correlated variables. In this test, the dependent variable is statistically associated with independent variables, which can be detected by GD. Results from the simulation test with 500 observations indicate that RID still outperforms OPGD in detecting the association between the dependent variable and interactions from both linearly and non-linearly correlated independent variables. Results demonstrating statistical associations with a comparison between RID and OPGD are shown in Table A1, and the visualization on simulated multiple variables is shown in Fig. A1. Parameters for both RID and OPGD in this simulation study are identical to those in the case study of road life expectancy analysis.

Table A1
RID tests on statistical associations between linearly and non-linearly correlated factors.

Variable / Interaction	PD by RGD / RID	PD by OPGD	Improvement by RGD / RID
Y~X1	0.108 (*)	0.041 (*)	0.067
Y~X2	0.118 (*)	0.103 (*)	0.015
Y~X3	0.087 (*)	0.056 (*)	0.031
Y~X4	0.102 (*)	0.071 (*)	0.031
Y~X1+X2	0.259	0.207	0.052
Y~X1+X3	0.216	0.111	0.105
Y~X1+X4	0.331	0.254	0.077
Y~X2+X3	0.212	0.177	0.035
Y~X2+X4	0.261	0.246	0.015
Y~X3+X4	0.318	0.202	0.116
Description of variables (*x* follows normal distributions)			
Y: dependent var	$y = a*x + b + noise$, *a and b are non-zero*		
X1: independent var	$y = a*x^2 + b + noise$, *a and b are non-zero*		
X2: independent var	$y = a*x*\sin(b*x) + c + noise$, *a and b and c are non-zero*		
X3: independent var	$y = a*x^2*\sin(b*x) + c + noise$, *a and b and c are non-zero*		
X4: independent var	$y = c*x + d + noise$, *c and d are non-zero*		

* : factor detector result statistically significant at $p < 0.05$.

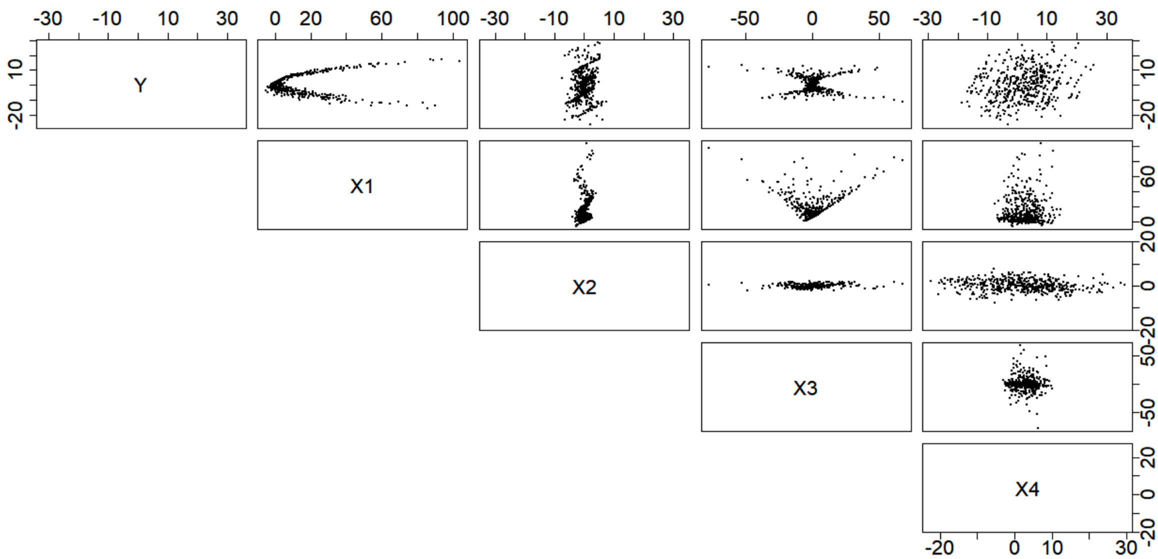

Fig. A1. Scatter plot matrix for simulation data with x and y axes represented by simulated variables.

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