INVESTIGATING THE IMPACT OF BIKE NETWORK INFRASTRUCTURE FEATURES ON CYCLIST SAFETY USING NETWORK THEORY INDICATORS[1]

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Abstract

Many cities worldwide are promoting cycling to create sustainable and livable communities. However, cyclists as vulnerable road users have elevated injury risk, which might deter road users from cycling. Previous research has found a significant association between bike network features and cyclist-vehicle crashes. Network analysis can be used to quantify features of the bike network that may affect cyclist safety. However, the application of network theory to bike network is not very well studied. This study introduces network indicators to measure the quality of bike network infrastructure at the macroscopic level and study its association with cyclist-vehicle crashes. This should help planners to a better understanding of bike network features effect on cyclist safety. The data used in this study was collected from 134 traffic analysis zones (TAZ's) in the City of Vancouver, Canada. Full Bayesian modeling incorporating spatial effect is employed to develop the crash models. The models showed that bike network length, weighted slope, and centrality have a negative association with cyclist-vehicle crashes, while bike network complexity, connectivity, and linearity have a positive association with cyclist-vehicle crashes. In addition, the results showed that cyclist-vehicle crashes were positively associated with vehicle kilometers traveled and bike kilometers traveled.

Introduction

Cyclists as vulnerable road users have elevated injury/fatality risk, which may deter road users from cycling. Therefore, understanding the underlying factors that affect cycling level and cyclist-vehicle crashes is essential for promoting cycling and increasing cyclist safety. Several studies developed bike safety models on the aggregate level and studied the impact of network size on bike safety. Wei and Lovegrove (2013) developed community-based macro-level crash models to investigate association between cyclist-vehicle crashes and the total network length, bike network length, number of bus stops, traffic signals, and intersection density, among others. Many studies investigated the association between network connectivity and cyclists' safety. Siddiqui et al. (2012), Strauss et al. (2013), and Wei and Lovegrove (2013) found a positive association between intersection density, network connectivity metric, and cyclist-vehicle crashes. Zhang (2015) investigated the effect of bike network indicators in the form of network centrality, clustering, average geodesic distance on non-motorist safety at TAZ's. They suggested that highly centered network is associated with less non-motorist crashes, and the higher clustering road networks are the lower the non-motorist crashes. Even though several research explored the association between network configuration and cyclist-vehicle crashes, limited research evaluated network theory indicators comprehensively and explored their association with cyclist-vehicle crashes (Osama and Sayed, 2016).

Network science is an academic field that studies complex networks such as social, computer, and biological networks. Kansky (1963) and Rodrigue et al. (2013) introduced indices that characterized transportation network connectivity, complexity, development, and accessibility. Previous studies showed that centrality has strong association with vehicle movements (Jiang, 2009; Jayasinghe et al., 2015). Zhang et al. (2011) applied three centrality measures on road network to explore the relationship between graphical and topological features of road network patterns at TAZ level. De Montis et al. (2007) introduced assortativity and rich-club coefficients to analyze interurban network characteristics using a weighted network analysis.

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This study employs full Bayesian techniques incorporating spatial effects to assess the effect of network indicators (centrality, assortativity, complexity, and robustness) on bike kilometers travelled and cyclist-vehicle crashes. The full Bayesian models are developed using data for 134 traffic analysis zones (TAZs) in the city of Vancouver.

Analysis variables

Definitions of the variables that are used in the analysis, and their summary statistics, are presented in Table 1. Degree centrality is calculated using Eq. (1), where $a_{ij} = 1$ only if node i and node j are connected by a link, and is equal to zero otherwise, and n is number of nodes in a network.Betweenness centrality is calculated using Eq. (2), where $g_{jk(i)}$ represents number of geodesics linking nodes $j$and k that contain point i on them, and g_{jk}represents number of geodesics linking nodes $j$and k.

$$C_i^D = \frac{1}{(n-1)} \sum_{i=1}^{n} \quad a_{ij} \tag{1}$$

$$C_i^B = \frac{1}{(n-1)(n-2)} \sum_{j}^{n} \sum_{k}^{n} \frac{g_{jk(i)}}{g_{jk}} i \neq j \neq k \tag{2}$$

Rich-club coefficient is calculated using Eq. (3), where $e_{>k}$ is the number of edges among the rich nodes (nodes with degrees greater than k), $n_{>k}$ denotes the number of rich nodes.Number of cycles is calculated using Eq. (4), where $e$is number of edges in a network, n is number of nodes in a network, and P is number of sub-graphs (Rodrigue et al., 2013).

$$Ri.Club = \frac{2e_{>k}}{n_{>k}(n_{>k}-1)} \tag{3}$$

$$NCycl = e - n + P \tag{4}$$

Two measures of connectivity are used in this study: network density and intersection density. Network density is the ratio between the total length of the bike links in a TAZ and the corresponding TAZ area. Intersection density is the ratio between the number of intersections in a TAZ and the area of the corresponding TAZ. Two measures are used to assess network directness: linearity and average edge length. A hypothetical length (modified bike network length) is calculated that represent the length of the bike network if all the links were straight, while preserving the nodes location. Then linearity is the ratio between the modified bike network length and the actual length of the bike network, at each TAZ. Average Edge Length is calculated as the ratio between the total length of the zonal bike network and the number of links in the corresponding TAZ (Kansky, 1963).

Methodology

For the crash models, Poisson lognormal models that account for spatial effects are employed to handle the over-dispersion in count data, and to account for both the unstructured and structured (spatially correlated) heterogeneities. The FB models development follows the procedure described in El-Basyouny and Sayed (2009). $Y_i$is assumed to be the number of crashes at zones, and it is assumed to follow a Poisson distribution with a parameter $\lambda_i$as shown in Eq. (6). $\lambda_i$is considered as a random variable and modeled as presented in Eq. (7).

$$Y_i \sim Poisson(\lambda_i) \tag{5}$$

$$\ln(\lambda_i) = a_o + a_1 \ln(VKT_i) + a_2 \ln(BKT_i) + b_i x_i + u_i + s_i \tag{6}$$

Where a_o, a_1, a_2, and b_i are model parameters, VKT_i is the vehicle exposure variable, BKT_i is the bike exposure variable, x_i represents the explanatory variables, u accounts for the unstructured heterogeneity among the zones, and $s_i$accounts for the spatially correlated heterogeneity among the zones.As implied from Eq. (6), and Eq. (7) u follows lognormal distribution. $\sigma_u^2$is the unstructured heterogeneity variation.

The spatial effect is modeled by Gaussian Conditional Autoregressive Regressive (CAR) techniques and calculated by Eq. (8).

$$u_i \sim Normal\,(0, \sigma_u^2) \tag{7}$$

$$S_i | S_{-i} \sim Normal\left(\overline{s_i}, \frac{\sigma_s^2}{n_i}\right), where \overline{s_i} = \sum_{j \epsilon C(i)} \frac{s_j}{n_i} \tag{8}$$

Table 1 Variables Definition and Data Summary (n = 134 TAZ)

Variable	Description	Mean	SD	Min	Max
Crashes					
Y	cyclist-vehicle crashes	12.72	13.49	0	78
Exposure					
VKT	Vehicle kilometer travelled (Km)	4.29	3.33	0.19	22.29
BKT	Bike Kilometer Travelled (Km)	1.05	2.11	0	21.46
Bike Network Indicators					
Centrality Indicators					
C^B	Betweenness Centrality	0.005	0.01	0	0.074
C^D	Degree Centrality	0.05	0.032	0.006	0.2
Assortativity Indicators					
Assort	Assortativity Coefficient	0.058	0.149	-0.333	0.525
Ri.Club	Rich-Club Coefficient	0.073	0.05	0.019	0.333
Complexity Indicators					
NCycl	Number of Cycles	1.388	1.414	0	6
Pi	Pi Index	190.415	107.6	0	791.306
Robustness Indicator					
ACC	Average Clustering Coefficient	0.0014	0.0062	0	0.0427
Connectivity Indicators					
NetD	Bike network Density	5.38	3.78	0	21.91
InterD	Intersection Density	74.28	33.797	6.077	235.954
Directness Indicators					
CAvgEdLen	Bike Network Average Edge Length	0.131	0.052	0	0.574
CLin	Bike Network Linearity	0.675	0.273	0	1
Topography Indicators					
CLen	Total Length of Bike Network Links (Km)	3.374	2.528	0	17.409
CSlope	Average Weighted Slope for Bike Network	2.525	0.902	0.639	6.657

Where, σ_s^2 is the spatial variation, n_i is the number of neighbors of zone i, $C(i)$ is the set of neighbors of zone i, S_i accounts for the spatially correlated (structured) heterogeneity among zones ,and S_{-i} is the set of all spatial effects except S_i. The spatial variation is assessed according to Eq. (9).

$$\psi_s = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_u^2} \tag{9}$$

Results

Tables 2 and 3 present the developed FB models. Spatial effects are significant in the entire developed models(i.e. $\psi_s \gg 0.5$). Moreover, the exposures exponent is positive and less than one, which indicates that higher exposure levels would reduce cyclist crash risk. This agrees with the "safety in numbers" hypothesis (Jacobsen, 2003). Betweenness and degree centralities are negatively associated with cyclist-vehicle crashes. The association between centrality and cyclist-vehicle crashes is consistent with previous research (Zhang et al., 2015) and is generally intuitive. Rich-club coefficient has a negative association with cyclist-vehicle crashes. Number of cycles has a positive association with cyclist-vehicle crashes. These results indicate that developed and complex network decreases cyclists' safety.

Network density and intersection density have positive associations with cyclist-vehicle crashes. This is plausible and consistent with previous research (Siddiqui et al., 2012; Strauss et al., 2013; Wei and Lovegrove, 2013; Osama and Sayed, 2016; Chen et al., 2018). Average edge length has a negative association with cyclist-vehicle crashes. This is consistent with previous study conducted by Quintero et al. (2013) on Metro Vancouver transit network. Linearity has positive association with cyclist-vehicle crashes. This is consistent with previous studies findings (Rome et al., 2014; Kaplan et al., 2014; Prato et al., 2016). As well, a negative association is found between the weighted slope of the zonal bike network and cyclist-vehicle crashes.

Table 2 Crash models 1&2 with spatial effects

	Model 1				Model 2			
	Estimate	SD	Credible Interval		Estimate	SD	Credible Interval	
			2.50%	97.50%			2.50%	97.50%
Intercept	1.774	0.231	1.304	2.213	2.793	0.219	2.360	3.225
BKT	0.522	0.062	0.403	0.643	0.538	0.070	0.397	0.675
CB	-22.220	8.514	-39.060	-5.500				
CD					-5.785	2.508	-10.820	-0.923
CLen					-0.061*	0.037	-0.135	0.012
InterD	0.003	0.001	-0.002	0.007				
NCycl					0.105	0.048	0.011	0.197
CLin	0.838	0.250	0.359	1.341				
DIC	746.757				748.235			
ψs	0.829	0.096	0.621	0.972	0.824	0.105	0.969	0.974

* Significantly different from zero at 10%.
All other variables were significantly different from zero at 5%.

Table 3 Crash models 3&4 with spatial effects

	Model 3				Model 4			
	Estimate	SD	Credible Interval		Estimate	SD	Credible Interval	
			2.50%	97.50%			2.50%	97.50%
Intercept	2.536	0.256	2.027	3.037	2.427	0.230	1.956	2.874
VKT	0.426	0.101	0.229	0.623	0.469	0.109	0.260	0.689
BKT	0.486	0.064	0.361	0.608	0.498	0.061	0.380	0.617
CLen	-0.094	0.036	-0.166	-0.024	-0.049*	0.031	-0.111	0.012
Ri.Club	-4.134	1.770	-7.673	-0.747				
CAvgEdLen					-2.947	1.450	-5.802	-0.105
DIC	744.469				744.341			
ψs	0.848	0.083	0.662	0.974	0.832	0.088	0.651	0.976

* Significantly different from zero at 10%.
All other variables were significantly different from zero at 5%.

Conclusion and summary

The developed crash models revealed that bike network length, centrality, assortativity, and continuity have a negative association with cyclist-vehicle crashes, while bike network complexity and development, connectivity, and linearity have positive association with cyclist-vehicle crashes. In addition, the results showed that cyclist-vehicle crashes were positively associated with vehicle kilometers travelled and bike kilometers travelled. This study has some limitations. The network theory indicators investigated in this study describe the bike network's infrastructure, but they do not account for the built environment context surrounding the bicycle network, such as land use, socio- economic, and road facility. The data in this study is a cross-sectional data; therefore, studies tracking cycling levels over time could provide a causal link between bike network infrastructure and cyclists' safety. Future research should investigate association of the network indicators presented with vehicle safety and pedestrian safety.

References

References available on request

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