

[Safety Science 79 (2015) 336–343](http://dx.doi.org/10.1016/j.ssci.2015.06.016)

Contents lists available at [ScienceDirect](http://www.sciencedirect.com/science/journal/09257535)

Safety Science

journal homepage: [www.elsevier.com/locate/ssci](http://www.elsevier.com/locate/ssci)



Built environment factors in explaining the automobile-involved bicycle crash frequencies: A spatial statistic approach



Peng Chen [⇑](#_bookmark0)

*Dept. of Urban Design and Planning, University of Washington, United States*

*Dept. of Civil and Environmental Engineering, University of Washington, United States*

# a r t i c l e i n f o

*Article history:*

Received 5 January 2015

Received in revised form 23 June 2015 Accepted 23 June 2015

*Keywords:*

Bicycle crash frequency Hierarchal Bayesian estimation

Poisson lognormal random effects model Built environment

Trafﬁc analysis zone

# a b s t r a c t

The objective of this study is to understand the relationship between built environment factors and bicycle crashes with motor vehicles involved in Seattle. The research method employed is a Poisson lognormal random effects model using hierarchal Bayesian estimation. The Trafﬁc Analysis Zone (TAZ) is selected as the unit of analysis to quantify the built environment factors. The assembled dataset provides a rich source of variables, including road network, street elements, trafﬁc controls, travel demand, land use, and socio-demographics. The research questions are twofold: how are the built environment factors associated with the bicycle crashes, and are the TAZ-based bicycle crashes spatially correlated? The ﬁndings of this study are: (1) safety improvements should focus on places with more mixed land use; (2) off-arterial bicycle routes are safer than on-arterial bicycle routes; (3) TAZ-based bicycle crashes are spatially correlated; (4) TAZs with more road signals and street parking signs are likely to have more bicycle crashes; and (5) TAZs with more automobile trips have more bicycle crashes. For policy implications, the results suggest that the local authorities should lower the driving speed limits, regulate cycling and driving behaviors in areas with mixed land use, and separate bike lanes from road trafﬁc.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Regular cycling activity generates physical and mental beneﬁts, such as losing weight, reducing stress and improving ﬁtness ([Clark](#_bookmark15) [et al., 1998](#_bookmark15)). An increase in the number of cyclists can reduce car dependence, demand for parking spaces, energy consumption, road congestion and trafﬁc related air-pollution. Increased popularity of cycling was observed as the number of bicycle trips doubled from

1.7 billion in 2001 to 4 billion in 2009 in the US ([U.S. Department of Transportation, 2009](#_bookmark20)). However, the percentage of cyclist fatalities steadily increased from 1.5% in 2003 to 2.2% in 2012 ([The National Highway Trafﬁc Safety Administration, 2012](#_bookmark20)). Cyclists are more vulnerable road users than motorists ([Wegman et al., 2012; Wei and Lovegrove, 2012](#_bookmark21)). Most of US cyclists inevitably rode close to vehicles on the roads, and plenty of cyclists were killed by cars even though they were wearing helmets. Even though cycling increased, overall the volume remains low in the US. Only 0.5% commuters rode bicycles in 2013 ([American Association of State Highway and Transportation Ofﬁcials and US Departmemt of Transportation, 2013](#_bookmark6)).

⇑ Address: 3949 15th Ave NE, Room 418, Gould Hall, Seattle, WA 98195, United States.

*E-mail address:* [chenp5@uw.edu](mailto:chenp5@uw.edu)

More research on the relationship between cycling safety and a built environment is needed in the US. Firstly, in explaining the causes of bicycle crashes, prior studies weighted behavioral factors, such as helmet use, as important elements ([Attewell et al., 2001;](#_bookmark7) [Walker, 2007](#_bookmark7)). Most of those studies were conducted at the micro-level focusing on individual cyclists. However, cyclists in the EU are not required to wear helmets and the bicycle crash risk is lower than that in the US ([Teschke et al., 2012](#_bookmark20)). Certain urban elements can explain the causes of bicycle collisions beyond behavioral factors. The macro area-based studies, which high- lighted the built environment effects, were greatly underestimated and insufﬁciently investigated ([Siddiqui et al., 2012](#_bookmark20)). Secondly, among the studies focused on built environment effects on bicycle crashes, many of them worked on bicycle route types ([Chen et al.,](#_bookmark11) [2012; Harris et al., 2011; Teschke et al., 2012](#_bookmark11)), while relatively less effort has been placed on area-wide built form land uses. Thirdly, because of the low density dispersed land use pattern, the high degrees of motorization and the low volume of cyclists in the US, research ﬁndings from other higher density countries may not be applicable to the US. Fourthly, research on behavioral factors pro- vides insights for education programs and policy enforcement to reshape driving and cycling behaviors. Research on built environ- ment factors contribute to lowering bicycle risks through

<http://dx.doi.org/10.1016/j.ssci.2015.06.016>

0925-7535/© 2015 Elsevier Ltd. All rights reserved.

*P. Chen / Safety Science 79 (2015) 336–343* 337

engineering modiﬁcations. Findings from the two types of research are mutually supportive.

The research objectives reported in this paper are twofold: (1) to explore the effects of built environment factors on bicycle crash frequencies at the TAZ level; (2) to account for the unobserved heterogeneity and spatial dependence among TAZs by modeling two random effects employing a Poisson lognormal model. The remainder of this paper is organized into four sections, starting with a review of the literature, followed by the description of data sources and geo-spatial unit selection, the descriptive and inferential analysis, and ending with a discussion, limitations and conclusions.

1. Literature review
   1. *Key deﬁnitions*

In this study, a ’bicycle crash’ is deﬁned as a collision between a bicycle and a motor vehicle. The ‘‘crash frequency,’’ also known as the ‘‘incidence,’’ is the number of collisions at a certain loca- tion/area per unit time. The ‘‘incidence rate’’, also known as the ‘‘risk’’, is calculated by the number of crashes reported per 1000 trips, 1000 h or 1 km of exposure. The exposure data is usually limited to trips, hours and kilometers cycled by each rider ([de Geus et al., 2012](#_bookmark17)). In this context, cycling risk is related to various types of built environment and behavioral risk factors. Risks can result in travel resistance such as perceived unsafety which has been found to affect travel behavior ([Schepers et al., 2013](#_bookmark28)).

* 1. *Relationships between built environment factors and bicycle crash* *frequency*

A large number of studies have investigated the relationships between built environment factors and bicycle crash frequency. The unit of analysis in prior research varies extensively, such as trafﬁc analysis zones ([Siddiqui et al., 2012; Wei and Lovegrove,](#_bookmark20) [2012](#_bookmark20)), census tracts ([Narayanamoorthy et al., 2013](#_bookmark22)), grid-based structures ([Gladhill and Monsere, 2012](#_bookmark18)) and locations ([Schepers](#_bookmark27) [et al., 2011; Strauss et al., 2013; Vandenbulcke et al., 2014;](#_bookmark27) [Wang and Nihan, 2004; Zahabi et al., 2011](#_bookmark27)). Besides, prior research has considered a large set of explanatory variables to investigate the relationships between the built environment and bicycle crash frequency, including the factors of road network, street elements, travel demand, trafﬁc controls, land use, and social-demographics. Regarding road network features, the densities of intersections, roadways and bike lanes have been included for modeling. For different types of intersections, positive associations between intersection density and bicycle crash frequency are conﬁrmed ([Siddiqui et al., 2012; Strauss et al., 2013; Wei and Lovegrove,](#_bookmark20) [2012](#_bookmark20)). In addition, complex intersections increase the likelihood of bicycle collisions ([Vandenbulcke et al., 2014](#_bookmark20)). As for the effects of roadway density, more drive lanes and bike lanes are positively associated with the number of bicycle crashes ([Wei and Lovegrove,](#_bookmark23) [2012](#_bookmark23)). Of different types of bicycle facilities, off-road bike lanes are safer than on-road bike lanes ([Hamann](#_bookmark19) [and](#_bookmark19) [Peek-Asa, 2013;](#_bookmark19) [Reynolds et al., 2009; Teschke et al., 2012](#_bookmark19)), and the installation of bicycle lanes does not lead to additional crashes, but a possible increase in the number of cyclists ([Chen et al., 2012](#_bookmark11)). [Sakshaug](#_bookmark24) [et al. (2010)](#_bookmark24) found that adding roundabouts produced more bicycle conﬂicts as the yielding rules were ambiguous in roundabout areas, contributing to a lower yielding rate and less trust among road users. By differentiating roundabouts at different locations, Daniels et al. found that roundabouts with cycle lanes performed worse than roundabouts in mixed trafﬁc and separated cycle paths

([Daniels et al., 2009](#_bookmark16)).

In terms of street elements, bus stop density is positively asso- ciated with bicycle crash occurrences ([Miranda-Moreno et al.,](#_bookmark22) [2011b; Strauss et al., 2013; Wei and Lovegrove, 2012](#_bookmark22)). Among current studies, street lighting has only been included for modeling bicycle injury severity ([Kim et al., 2007; Klop and Khattak, 1999](#_bookmark22)), but barely been considered for bicycle crash frequency. Moreover, parking entrance shows an insigniﬁcant relationship with bicycle crash frequency ([Miranda-Moreno et al., 2011b](#_bookmark22)), but parked vehicles close to separated bike facilities are associated with an increased risk ([Vandenbulcke et al., 2014](#_bookmark20)).

Among the travel demand variables, vehicle volume ([Hamann](#_bookmark19) [and Peek-Asa, 2013; Schepers et al., 2011](#_bookmark19)), bicycle volume ([Hamann](#_bookmark19) [and](#_bookmark19) [Peek-Asa, 2013;](#_bookmark19) [Miranda-Moreno et al., 2011b;](#_bookmark19) [Schepers et al., 2011; Strauss et al., 2013](#_bookmark19)) and large vehicle volume ([Vandenbulcke et al., 2014](#_bookmark20)) have been included for modeling, and all of them suggest positive associations with bicycle crash fre- quency. As for trafﬁc control variables, a higher density of low-speed streets (<15 mph) is negatively associated with the number of bicycle crashes ([Siddiqui et al., 2012](#_bookmark20)), while more roads with high-speed limits (>35 mph) have an increased number of bicycle crashes ([Chen and Fuller, 2014; Siddiqui et al., 2012](#_bookmark12)). Additionally, trafﬁc signal density is positively correlated with the occurrences of bike collisions ([Wei and Lovegrove, 2012](#_bookmark23)).

In relation to land use factors, percentage of commercial land

use and proximity to it were positively associated with bicycle crash frequency and cyclist evident injuries ([Narayanamoorthy](#_bookmark22) [et al., 2013; Vandenbulcke et al., 2014](#_bookmark22)), but percentage of commer- cial land use was not a signiﬁcant predictor of bicycle crashes in Strauss et al.’s study (2012). Inconsistencies remain in the effects of land use factors. Regarding socio-demographic factors, Siddiqui et al.’s study showed that the densities of population and employment were positively related to bicycle crash frequency (2012).

* 1. *Modeling techniques*

The concerns of crash frequency modeling include over-dispersion or under-dispersion of the count data, unobserved heterogeneity, spatial dependence, and the excess of zeros ([Lord](#_bookmark22) [and Mannering, 2010; Mannering and Bhat, 2014](#_bookmark22)). The basic model used in bicycle crash frequency research is the negative binomial (NB) regression, which can handle data over-dispersion. Zero-inﬂated models can account for the excess of zeros by jointly working with the Poisson or NB model. The generalized additive model and random effects model can calculate spatial dependence. Bivariate and multivariate models have become increasingly popular, since they can split the crash frequency matching with speciﬁc classiﬁcations. For instance, bicycle crashes can be categorized by injury severity, spatial locations and time periods. The above modeling advantages can be joined, such as the Poisson-lognormal conditional-autoregressive model ([Wang and](#_bookmark20) [Kockelman, 2013](#_bookmark20)) and the Bayesian multivariate Poisson lognor- mal model ([Aguero-Valverde and Jovanis, 2009; Park and Lord,](#_bookmark8) [2007](#_bookmark8)). The spatial statistic approach provides a chance to capture the spatial autocorrelation with accurately estimated parameters. It contributes to the generalizability that same treatments can be applied to areas with similar features.

1. Model speciﬁcation

This study employs an area-based Poisson lognormal random effects model. It has two attractive features: handling over-dispersion of count data, and accounting for unobserved heterogeneity and spatial dependence. It provides the estimates

338 *P. Chen / Safety Science 79 (2015) 336–343*

of subject-speciﬁc conditional probability compared to aggregated population parameters in other models.

The Poisson lognormal random effects model is becoming popular in crash frequency research. Fixing the random effects can improve the model ﬁt and the precision of posterior estimates ([Aguero-Valverde, 2013](#_bookmark9)). The marginal distribution of the Poisson lognormal model does not have a closed form; hence, it is implemented with the hierarchal Bayesian estimation. The model is presented in Eq. [(1)](#_bookmark1):

*Yi*j*a*; *bi* ; *ui*; *mi* ~ *Poisson*ð*ea*þ*bi Xi eui* þ*mi* Þ ð1Þ

The model includes an intercept *a* and a vector of estimated parameters *bi* for the ﬁxed effects. *Yi* is the dependent variable of bicycle crashes. *Xi* is the vector of the independent variables. The unknown quantities are the coefﬁcients of the vectors of *ui* and *vi*, which are two latent random effects to compose the posterior distributions of spatial variance (*ui*) and unobserved heterogeneity (*vi*).

2.97%. The data had ﬁve types of injuries, including fatality (dead at scene/on arrival/in hospital), serious injury, evident injury, pos- sible injury and property damage only.

Policemen reported crash data has limitations because a large number of minor incidents are unreported to authorities ([de](#_bookmark17) [Geus et al., 2012; Wegman et al., 2012](#_bookmark17)). The possible biases included are: (1) less severe crashes, including property damages, possible injuries and evident injuries, are widely underestimated;

(2) collisions that occurred at local streets and remote areas are relatively under surveillance; and (3) collisions between cyclists, conﬂicts between cyclists and pedestrians, and single falls are not covered in the sample.

*4.2. Risk factors*

Bicycle crash frequency results from the interaction of three trafﬁc safety pillars: road user(s), bicycle(s) or vehicle(s), and built environment ([Schepers et al., 2013](#_bookmark28)). Risk factors are

deﬁned as any built environment features or risk-taking travel

*ui*j*uj*; *j* 2

*ne*ð*i*Þ~ *N*(*u*

*r*2

*i*; *mi*

*u*

2 behaviors that increase the likelihood of a bicycle crash. The built environment data is supported by Puget Sound Regional

Council (PSRC), SDOT and King County (KC). The sources,

X¼ ð Þ*i j*

ð Þ

*u* 1 *u* 3

*mi j*2*ne*ð*i*Þ

Eqs. [(2) and (3)](#_bookmark1) describe the random effects employed to estimate the spatial dependence. *ui* is the local spatial random effects assumed to follow a lognormal distribution. To deﬁne a neighbor, *ne*(*i*) is the set of adjacent polygons of area *i*, and *mi* is the number of neighbors of area *i*. The neighbors are deﬁned by at least sharing one border. Speciﬁcally, for area *i*, the variance of *ui* is conditional on *uj*, and *j* e *ne*(*i*). This model assigns the spatial random effects an intrinsic conditional on the autoregressive prior. The spatial

random effect’s mean is the mean of the neighboring TAZs, and the variance is proportional to one over the number of its neighbors. This approach was developed by [Besag et al. (1991)](#_bookmark13).

*vi* ~ *N*ð0; *r*2 Þ ð4Þ

*v*

where *vi* represents the random effects of the unobserved hetero- geneity, assuming it follows independent and identical distribution, as indicated in Eq. [(4)](#_bookmark2). *vi* captures the residual or unexplained log frequency of collisions in area *i*, where the variance *r*2 controls the extra-Poisson variation ([Aguero-Valverde, 2013](#_bookmark9)). Both *r*2 and

*v*

*u*

*r*2 are deﬁned with respect to the log scale. *r*2 is a conditional vari-

explanations, and data summary of selected variables are listed in [Table 1](#_bookmark3).

The built environment factors have six components, including road network, trafﬁc controls, street elements, travel demand, land use and socio-demographics, aggregated in the TAZs. The road network includes 3-way intersections, 4-way intersections and complicated intersections (more than 5 ways), the densities of on-arterial vs. off-arterial bike routes, and zonal mean slope. The trafﬁc control variables include the densities of road signals and stop signs, and zonal mean of driving speed limits. The zonal mean of driving speed limit is equal to the length of road segment multiplied by the corresponding posted speed limit, and divided by the sum length of roads. The street elements are the densities of bus stops, street lights, street trees and roundabouts. The density of crosswalks, and the densities of local streets vs. arterials are excluded due to collinearity. The land use factors are land-use mixture, the percentage of commercial and mixed lands, the percentage of ofﬁce and government lands, and the percentage of industrial lands. The socio-demographic factors include household density and employment density. The number of households and the number of jobs are excluded also for collinearity.

*v u* Additionally, three travel demand variables are included for

ance and its magnitude determines the amount of spatial variation, whereas *r*2 has a marginal interpretation. Bayesian inference is carried out through the R INLA package. INLA is short for integrated nested Laplace approximation.

*v*

1. Data sources and geo-unit selection

The geographical boundary of this study is the city of Seattle. As a bicycle friendly city, Seattle Department of Transportation (SDOT) has been working steadily toward developing an urban bicycle trail system to accommodate cyclists. Additionally, the bicycle share program was launched from October 2014 to further encourage cycling. To better understand bicycle safety, the data employed for this research include two components, bicycle crash records and built environment factors.

* 1. *Bicycle-motor crash data*

The bicycle crash data was collected by SDOT from 2010 to 2013. The bicycle crash data had 1389 records. In that 4-year period, the total number of automobile involved crashes in Seattle was 46,797, and the percentage of bicycle crashes was

modeling. The number of bicycle trips and total trips are esti- mated by PSRC ([Puget Sound Regional Council, 2014](#_bookmark25)), which are a part of the output of an activity-based travel forecasting model, called SoundCast. The number of bicycle trips and total number of trips are major outputs of this model. The original data were surveyed and gathered by PSRC. Trafﬁc volume (annual average daily trafﬁc, AADT) and the number of lanes are not included for this research, because Seattle only has those data for arterials. The cyclist volume and bicycle miles travelled are not available in Seattle. In this study, the number of bicycle trips acts as a substitute for cyclist volume, while the total num- ber of trips is a substitute for trafﬁc volume. Bike mode share is calculated by the number of bicycle trips divided by the total number of trips in TAZs. The use of these travel demand variables is novel in measuring bicycle exposure.

* 1. *Geo-spatial analytical unit selection*

The geographical unit in quantifying built environment and aggregating crash occurrences varied in prior crash studies, such as county ([Aguero-Valverde and Jovanis, 2006; Huang et al.,](#_bookmark10) [2010](#_bookmark10)), census tract ([Ukkusuri et al., 2012](#_bookmark20)), TAZ ([Siddiqui et al.,](#_bookmark20)

*P. Chen / Safety Science 79 (2015) 336–343* 339

Table 1

Variable deﬁnitions and data summary (*n* = 707) of potential predictors for bicycle crashes in Seattle TAZ average.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable | Mean | S.D. | Min. | Max. | Unit | Source |
| *Crash* |  |  |  |  |  |  |
| The number of bicycle crashes | 1.97 | 2.58 | 0.00 | 28.00 | num/TAZ | SDOT |
| *Road network* |  |  |  |  |  |  |
| Number of 3-way intersections per ha | 0.31 | 0.26 | 0.00 | 1.75 | num/ha | PSRC |
| Number of 4-way intersections per ha | 0.46 | 0.34 | 0.00 | 2.28 | num/ha | PSRC |
| Number of complicated intersections (>5 ways) per ha | 0.04 | 0.14 | 0.00 | 1.33 | num/ha | PSRC |
| Number of roundabouts per ha | 0.06 | 0.09 | 0.00 | 0.51 | num/ha | SDOT |
| Length of local streets per ha | *0.03* | *0.03* | *0.00* | *0.17* | km/ha | SDOT |
| Length of arterials per ha | *0.08* | *0.05* | *0.00* | *0.32* | km/ha | SDOT |
| Length of on-arterial bike lanes per ha | 0.02 | 0.02 | 0.00 | 0.19 | km/ha | SDOT |
| Length of off-arterial bike lanes per ha | 0.04 | 0.03 | 0.00 | 0.20 | km/ha | SDOT |
| Zonal mean slope (average gradients, absolute value) | 0.21 | 0.33 | 0.00 | 4.11 | ratio | SDOT |
| *Street elements* |  |  |  |  |  |  |
| Number of bus stops per ha | 0.26 | 0.31 | 0.00 | 2.74 | num/ha | KC |
| Number of street lights per ha | 5.12 | 2.22 | 0.00 | 15.48 | num/ha | SDOT |
| Number of street trees per ha | 8.53 | 6.26 | 0.00 | 31.46 | num/ha | SDOT |
| Number of parking signs per ha | 4.36 | 6.97 | 0.00 | 43.4 | num/ha | SDOT |
| *Trafﬁc controls* |  |  |  |  |  |  |
| Number of stop signs per ha | 0.50 | 0.43 | 0.00 | 2.87 | num/ha | SDOT |
| Zonal mean of driving speed limits | 25.25 | 4.53 | 20.00 | 48.08 | mph | SDOT |
| Number of trafﬁc signals per ha | 0.19 | 0.34 | 0.00 | 2.13 | num/ha | SDOT |
| *Travel demand* |  |  |  |  |  |  |
| Bike mode share | 0.02 | 0.02 | 0.00 | 0.18 | ratio | PSRC |
| Number of bicycle trips in TAZs | 0.07 | 0.17 | 0.00 | 3.68 | 103 | PSRC |
| Total number of trips in TAZs | 3.55 | 2.98 | 0.03 | 40.86 | 103 | PSRC |
| *Land use* |  |  |  |  |  |  |
| Land-use mixture, ranging from 0 to 1 | 0.51 | 0.15 | 0.00 | 0.87 | ratio | PSRC |
| Percentage of industrial lands in TAZs | 0.07 | 0.14 | 0.00 | 0.91 | ratio | PSRC |
| Percentage of commercial and mixed lands in TAZs | 0.10 | 0.15 | 0.00 | 0.81 | ratio | PSRC |
| Percentage of ofﬁce and government lands in TAZs | 0.10 | 0.15 | 0.00 | 0.83 | ratio | PSRC |
| Area of each TAZ | *0.31* | *0.33* | *0.01* | *3.37* | km2 | SDOT |
| *Socio-demographic*  Household density | 0.02 | 0.03 | 0.00 | 0.18 | 103/ha | PSRC |
| Employment density | 0.09 | 0.23 | 0.00 | 2.09 | 103/ha | PSRC |
| Number of households in the TAZs | *402.21* | *352.24* | *0.00* | *2181* | num/TAZ | PSRC |
| Number of jobs in the TAZs | *680.36* | *954.75* | *0.00* | *17,304* | num/TAZ | PSRC |

The variables in *italics* are excluded in modeling due to collinearity.

[2012; Wei and Lovegrove, 2012](#_bookmark20)), grid-cell ([Gladhill and Monsere,](#_bookmark18) [2012](#_bookmark18)) and intersection ([Castro](#_bookmark14) [et al., 2012;](#_bookmark14) [Miranda-Moreno](#_bookmark14) [et al., 2011a; Vandenbulcke et al., 2014](#_bookmark14)). There is a trade-off when a geographical scale is chosen. Larger areas provide more stable rates, but the accuracy of measurements may be reduced due to aggregation. A large geospatial unit may have the threat of regres- sion toward the mean. Some localized effects can only be detected on a small scale.

This study takes the TAZ as the analytical unit for two reasons. Firstly, it is a reasonable scale in which detailed built environment variations can be observed. Secondly, it matches the census infor- mation of important socio-demographic proﬁles and travel demand characteristics, including population density, employment density, bike mode share, the number of bicycle trips and the total number of trips.

Another challenge is the possible error of counting the occurrences of bicycle crashes. A collision may just fall into the cross-boundary between two neighboring TAZs. For instance,

deviation of 2.58 collisions, suggesting that the distribution of the bicycle crash frequency is dispersed. As indicated in [Fig. 1](#_bookmark4), more collisions are clustered in downtown Seattle.

1. Results

[Table 2](#_bookmark5) lists the outcome of the Poisson lognormal random effects model using hierarchal Bayesian estimation. The estimates at 2.5% and 97.5% credential intervals with no possible zero parameter are signiﬁcant factors for interpretation. These factors are: the 3-way intersection density, the density of on-arterial bike lanes vs. off-arterial bike lanes, the densities of road signals and parking signs, the zonal mean of driving speed limits, the land-use mixture, and the total number of trips.

The spatial dependence is calculated based on the variance of the two random effects. This dependence shows the proportion of model error explained by the spatial random effects through

TAZs are usually split by the arterials, and many bicycle crashes

occurred on arterials. An inaccurate geo-coding error may result

the relationship of, *ru*

*u* þ*rv*

*r*

accounting for 54.50% of all variance.

in the change of counted crash occurrences among TAZs. This study uses ‘‘spatial join’’ function in the ArcGIS to count bicycle crashes, assuming that the data was correctly geo-coded by SDOT.

* 1. *Descriptive analysis*

The dependent variable is bicycle crash frequency, ranging from

0.00 to 28.00, with a mean of 1.97 collisions and a standard

This model indicates that more than half of the errors can be explained by the spatial autocorrelation or spatial spillover effects. It also suggests 45.50% of unobserved heterogeneities remain. The same modiﬁcations can be applied to areas with similar built envi- ronment features to reduce bicycle crash frequencies.

In the outcome of the Poisson lognormal random effects model, the 3-way intersection density and the density of off-arterial bike lanes suggest negative relationships with the number of bicycle crashes. The density of road signals, the density of street parking

340 *P. Chen / Safety Science 79 (2015) 336–343*

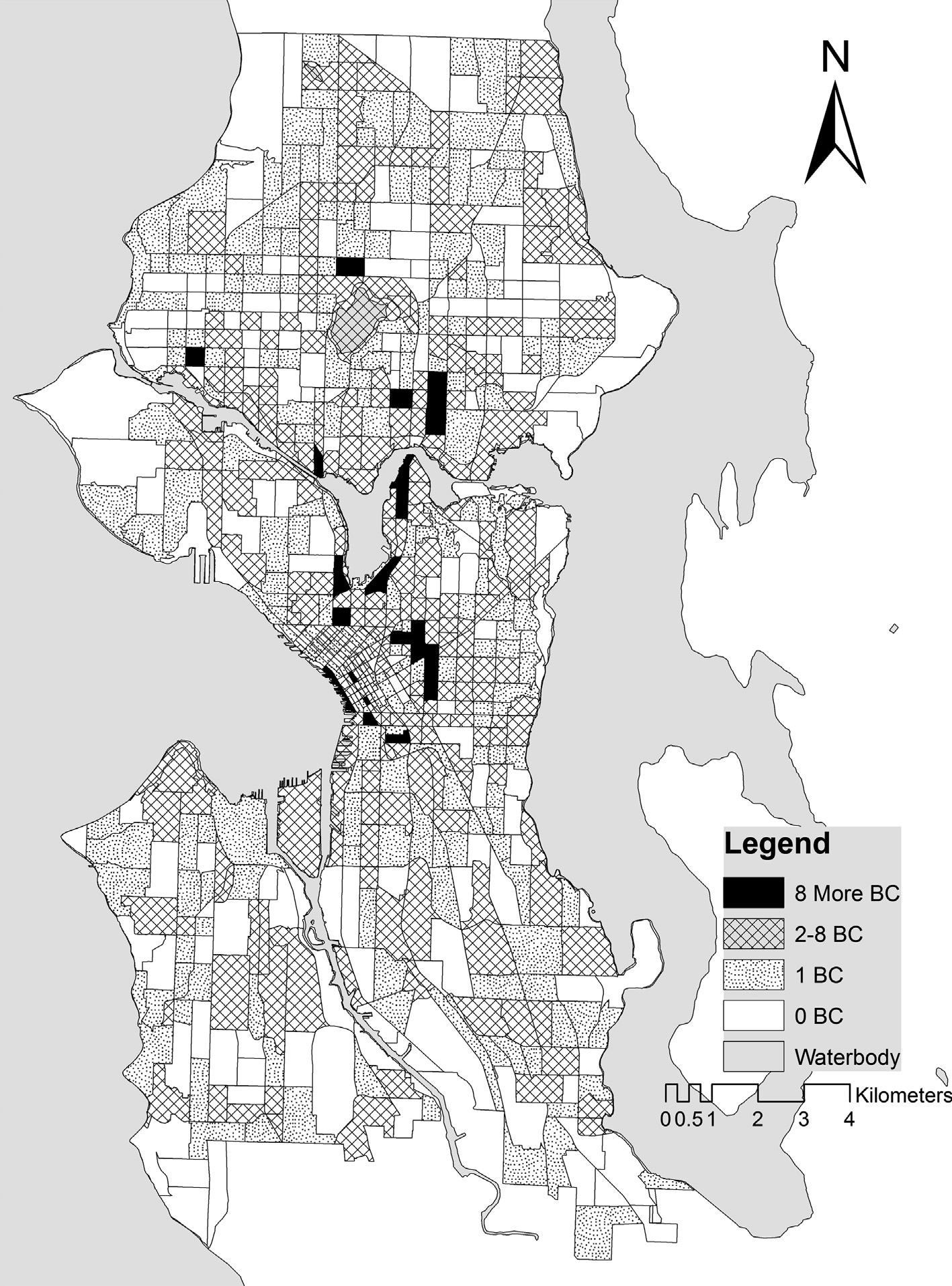


Fig. 1. Bicycle crashes in Seattle trafﬁc analysis zones, 2010–2013.

signs, the zonal mean of driving speed limits, the total number of trips, the land-use mixture, and the density of on-arterial bike lanes are positively correlated with the number of bicycle crashes. The elasticity is computed as the regression parameter times the mean value of the variable ð*E* ¼ *b*\**i Xi*Þ. None of the calculated

elasticity is more than 1.0. The elasticity suggests that the modiﬁ-

cations on one single built environment factor have limited effects in lowering the cycling risks.

1. Discussion

The purpose of this study is to examine how built environment factors are related to bicycle crashes, particularly to identify the modiﬁable factors that contribute to better cycling safety. In rela- tion to road network, the modeling outcomes suggest that the 3-way intersection density is negatively associated with bicycle crash frequency. The effects of the 4-way and complicated inter- sections remain unclear. However, some prior research found

positive relationships between bicycle crash frequency and inter- section density/counts ([Siddiqui et al., 2012; Wei and Lovegrove,](#_bookmark20) [2012](#_bookmark20)). There is a possible explanation for this inconsistency. The exposure to encounters between intersecting vehicles increase as the number of intersections increase; however, road networks with more intersections may contribute to lower driving speeds and thereby lessen severe bicycle crashes. Hence, the results are mixed. For the effects of different bicycle routes, the results are consistent with past research ([Lusk et al., 2013; Teschke et al.,](#_bookmark22) [2012; Wei and Lovegrove, 2012](#_bookmark22)). Cycling on on-arterial bike lanes is more dangerous than cycling on off-arterial bike lanes.

The outcome shows that a higher zonal mean of driving speed limits is associated with more bicycle crashes. The elasticity is 0.81% of bicycle crashes for a 1.0% increase in the zonal mean of driving speed limits. Prior area-based research did not include zonal mean of driving speed limits as risk factors. However, other micro-level bicycle injury severity studies suggested that higher driving speed limits resulted in more severe bicycle collisions

*P. Chen / Safety Science 79 (2015) 336–343* 341

Table 2

The estimates of the Poisson lognormal random effects model with 4-year bicycle crash data and the elasticity for signiﬁcant variables.

Fixed effects Estimate 95% Credible interval Elasticity Mean S.D. 2.5% CI 97.5% CI

Intercept -1.314 0.431 -2.161 -1.314

*Road network*

Number of 3-way intersections per ha -0.371 0.168 -0.702 -0.043 -0.115

Number of 4-way intersections per ha -0.570 0.322 -1.207 0.057

Number of complicated intersections per ha -0.201 0.190 -0.574 0.171

Number of roundabouts per ha -0.146 0.549 -1.229 0.926

Length of on-arterial bike lanes per ha 0.005 0.003 0.000 0.011 0.000

Length of off-arterial bike lanes per ha -0.008 0.003 -0.014 -0.001 0.000

Zonal mean slope -0.303 0.184 -0.672 0.053

*Street elements*

Number of bus stops per ha 0.272 0.176 -0.074 0.616

Number of street lights per ha 0.025 0.025 -0.024 0.074

Number of street trees per ha -0.007 0.009 -0.024 0.010

Number of parking signs per ha 0.032 0.012 0.009 0.054 0.140

*Trafﬁc controls*

Number of stop signs per ha 0.129 0.127 -0.122 0.378

Zonal mean of driving speed limits 0.032 0.012 0.009 0.054 0.808

Number of trafﬁc signals per ha 0.621 0.217 0.195 1.047 0.118

*Travel demand*

Bike mode share 4.057 4.589 -5.289 12.750

Number of bicycle trips -0.595 0.373 -1.333 0.134

Total number of trips 0.065 0.025 0.016 0.113 0.231

*Land use*

Entropy of mixing land use 1.208 0.347 0.527 1.887 0.616

Percentage of industrial lands -0.030 0.430 -0.878 0.811

Percentage of commercial and mixed lands 0.286 0.374 -0.445 1.024

Percentage of ofﬁce and government lands 0.126 0.369 -0.600 0.849

*Socio-Demographics*

Household density -2.761 1.667 -6.048 0.500

Employment density -0.024 0.255 -0.529 0.474

Random Effects Mean S.D. 2.5% CI 97.5% CI

*rv* 8.301 3.419 3.979 17.098

*ru* 0.933 0.231 0.527 1.430

Marginal Likelihood -1963.59

Spatial Dependence *r ru*

0.545

*u* þ*rv*

([Chen and Fuller, 2014; Eluru et al., 2008; Kim et al., 2007;](#_bookmark12) [Zahabi et al., 2011](#_bookmark12)). In short, all research indicates that lowering driving speed limits is an effective approach to reduce cycling risks.

The results on trafﬁc signals are consistent with past research ([Wei and Lovegrove, 2012](#_bookmark23)); higher signalized intersection density is associated with more bicycle crashes. Furthermore, a positive association between the density of street parking signs and bicycle crash occurrences is also conﬁrmed by this study. A similar conclu- sion from one prior study showed that parked cars next to bike facilities were related to an increased crash risk ([Vandenbulcke](#_bookmark20) [et al., 2014](#_bookmark20)).

In relation to land uses, a study showed that industrial and commercial land uses were positively related to bicycle injuries ([Narayanamoorthy et al., 2013](#_bookmark22)), but those results remain unclear with Seattle’s data. Land-use mixture has barely been investigated in prior bicycle crash frequency studies. This study suggests that a 1.0% increase in the land-use mixture is associated with a 0.62% increase in the number of bicycle crashes. This positive relationship may result from the conﬂicts between concentrated human activities in places with different land use purposes.

This study used the total number of trips as a substitute for traf- ﬁc volume. Even though the variables are different, the ﬁndings are somewhat consistent ([Miranda-Moreno et al., 2011a,b; Chen and](#_bookmark22) [Fuller, 2014; Vandenbulcke et al., 2014](#_bookmark22)). A positive relationship between the total number of trips and bicycle crashes is identiﬁed in this study.

1. Limitations

Some limitations of this study should be noted. A major challenge comes from the trend confounding effect across a 4-year period. Trafﬁc controls are time-varying explanatory variables so that the temporal effects of trafﬁc signals are hard to control. For instance, the signals could have been installed after the crashes had occurred, which could be a plausible alternative explanation for the positive association between bicycle crashes and number of signals. A similar case can be found in the interpre- tation of the relationship between bicycle crashes and on-arterial bike lanes. The government may have given higher priority to improving the bicycle infrastructures where crashes had occurred. Because the order of the events cannot be conﬁrmed, uncertainty remains in the interpretation. A possible way to control this con- founding effect is to add random effects for space–time modeling. However, the space–time model assumes that the crash risks in the temporal trends are linear ([Knorr-Held and Besag, 1998](#_bookmark22)). This assumption does not apply to SDOT bicycle crash data. Also, the sample is too small to be further split, and bicycle crash counts in TAZs are likely to have the problem of excess of zeros. Furthermore, it is not cost-effective for authorities to update built environment data annually.

The second challenge comes from the underreporting/un

der-surveillance and unavailability of data used in this study. Firstly, there are many unreported minor bicycle collisions, espe- cially in suburban areas and local streets. This underreporting of

342 *P. Chen / Safety Science 79 (2015) 336–343*

bicycle crash counts poses a threat to the reliability of the data. Similarly, the trafﬁc volume data is only gathered at arterials and freeways, but missing on local streets. Secondly, data unavailability could have a negative effect on the accuracy of modeling. For instance, this study suggests that the density of on-arterial bike lanes is positively correlated with bicycle crash frequency. This conclusion could be impacted by missing cyclist volume data. Bicycle miles travelled and cyclist volume are more accurate in describing the distance cyclists travelled and the number of on-road cyclists. Better data should be gathered to enrich future bicycle crash research.

It remains questionable whether ﬁndings generalized from

Seattle are applicable for other US cities. This is because, ﬁrstly, Seattle is a city of relatively high density, posing a threat to the generalizability to the other low density cities. It is likely that these results apply the best to other central downtown areas. Secondly, Seattle continually implements bicycle master plan and cycle share program to promote cycling as a primary transportation mode. It may not be an appropriate inference for cities having much lower cyclist volume.

1. Conclusions

The popularity of cycling is greatly attached to cycling safety. Lowering bicycle crash risk is a key step in reducing the resistance to riding bicycles and in promoting cycling as an active mode of transportation. To address possible concerns about the safety ramiﬁcations of increased bicycle use in the North America, this research evaluates bicycle safety in an urban environment.

From the methodological point of view, the regression techniques employed in this study highlight the importance of measuring spatial dependence and unobserved heterogeneity. The results indicate that zonal bicycle crash frequencies are spa- tially correlated. This study has included some bicycle exposure variables that had not been investigated in prior studies. Unique variables include the number of bicycle trips vs. the total number of trips, the zonal mean of driving speed limits, the zonal mean slopes, and the densities of street trees and parking signs. The signiﬁcance of these new information help us to better understand the exposure and risks of cycling behaviors. However, in light of the data limitations in the bicycle exposure measurements, future research with improved data is needed to verify some of the results.

For transportation engineers, planners and policy makers, this

research provides several statistically founded recommendations to improve bicycle safety through engineering modiﬁcations. For instance, local authorities should lower the driving speed limits, regulate cycling and driving behaviors in areas with mixed land use, and separate bike lanes from road trafﬁc. Additionally, the incentive of speed limit reduction for bicycle safety is to decrease actual driving speeds. For good roadway design practices, transport engineers should apply the principles of ‘‘Vision Zero’’ ([Tingvall](#_bookmark20) [and Haworth, 2000](#_bookmark20)), and ‘‘functionality, homogeneity and pre- dictability’’ ([Wegman et al., 2005](#_bookmark26)) to operate a sustainably safe trafﬁc system. These principles and measures are generally not efﬁcient when implemented on their own. Whether the joint effects of multiple factors can promote bicycle safety greatly need to be further studied. If properly implemented, programs and poli- cies resulting in improvements in bicycle safety could in turn address the social concerns on mobility and sustainability of trans- portation. To improve individual health, in view of the widely ongoing planning and construction to promote increased cycling in the North America, continual research for bicycle crashes is urgently needed. Safety cannot be traded for the sake of mobility ([Tingvall and Haworth, 2000](#_bookmark20)).

Note

1. LUM: land-use mixture or the degrees of mixing land use, which is measured by

## LUM ¼- X *i* ¼ ln Pi \* ðln Pi=ln nÞ

where *n* is the number of different land use type classes in the TAZ and Pi is the proportion of land in type *i* in the TAZ. This index is calculated separately for each TAZ. The resulting variable LUM is the land use mix entropy index, which varies from 0 (homoge- neous land use) to 1 (most mixed) land use.

Acknowledgements

The author acknowledges the comments from two anonymous reviewers on literature review, statistical modeling and policy implications, Professor Qing Shen on conceptual framework, as well as supportive staff of sharing data and explaining codes by Dana Trethewy and Craig Moore from SDOT, and Suzanne Childress from PSRC.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ssci.2015.06.016>.

References

[Aguero-Valverde, J., 2013. Full Bayes Poisson gamma, Poisson lognormal, and zero](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0005) [inﬂated random effects models: comparing the precision of crash frequency](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0005) [estimates. Accid. Anal. Prev. 50, 289–297](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0005).

[Aguero-Valverde, J., Jovanis, P.P., 2006. Spatial analysis of fatal and injury crashes in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0010) [Pennsylvania. Accid. Anal. Prev. 38, 618–625](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0010).

[Aguero-Valverde, J., Jovanis, P.P., 2009. Bayesian multivariate Poisson lognormal](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0015) [models for crash severity modeling and site ranking. Transport. Res. Record: J.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0015) [Transport. Res. Board 2136, 82–91](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0015).

American Association of State Highway and Transportation Ofﬁcials and US Departmemt of Transportation, 2013. Commuting in America 2013: The National Report on Commuting Patterns and Trends. 7–8.

[Attewell, R.G., Glase, K., McFadden, M., 2001. Bicycle helmet efﬁcacy: a meta-](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0025) [analysis. Accid. Anal. Prev. 33, 345–352](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0025).

[Besag, J., York, J., Mollié, A., 1991. Bayesian image restoration, with two applications](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0030) [in spatial statistics. Ann. Inst. Stat. Math. 43, 1–20](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0030).

[Castro, M., Paleti, R., Bhat, C.R., 2012. A latent variable representation of count data](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0035) [models to accommodate spatial and temporal dependence: application to](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0035) [predicting crash frequency at intersections. Transport. Res. Part B: Methodol.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0035) [46, 253–272](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0035).

[Chen, D., Fuller, D., 2014. Analyzing road surface conditions, collision time, and road](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0040) [structural factors associated with bicycle collisions from 2000 to 2010 in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0040) [Saskatoon, Saskatchewan. J. Transport Health 1, 40–44](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0040).

[Chen, L., Chen, C., Srinivasan, R., McKnight, C.E., Ewing, R., Roe, M., 2012. Evaluating](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0045) [the safety effects of bicycle lanes in New York City. Am. J. Public Health, 102](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0045).

[Clark, A., Thornley, B., Tomlinson, L., Galletley, C., Norman, R.J., 1998. Weight loss in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0050) [obese infertile women results in improvement in reproductive outcome for all](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0050) [forms of fertility treatment. Hum. Reprod. 13, 1502–1505](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0050).

[Daniels, S., Brijs, T., Nuyts, E., Wets, G., 2009. Injury crashes with bicyclists at](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0055) [roundabouts: inﬂuence of some location characteristics and the design of cycle](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0055) [facilities. J. Safety Res. 40, 141–148](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0055).

[de Geus, B., Vandenbulcke, G., Int Panis, L., Thomas, I., Degraeuwe, B., Cumps, E.,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0060) [Aertsens, J., Torfs, R., Meeusen, R., 2012. A prospective cohort study on minor](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0060) [accidents involving commuter cyclists in Belgium. Accid. Anal. Prev. 45, 683–](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0060) [693](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0060).

[Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0065) [model for examining pedestrian and bicyclist injury severity level in trafﬁc](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0065) [crashes. Accid. Anal. Prev. 40, 1033–1054](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0065).

[Gladhill, K., Monsere, C.M., 2012. Exploring trafﬁc safety and urban form in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0070) [Portland, Oregon. Transport. Res. Record: J. Transport. Res. Board 2318, 63–74](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0070). [Hamann, C., Peek-Asa, C., 2013. On-road bicycle facilities and bicycle crashes in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0075)

[Iowa, 2007–2010. Accid. Anal. Prev. 56, 103–109](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0075).

[Harris, M.A., Reynolds, C.C., Winters, M., Chipman, M., Cripton, P.A., Cusimano, M.D.,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0080) [Teschke, K., 2011. The Bicyclists’ Injuries and the Cycling Environment study: a](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0080) [protocol to tackle methodological issues facing studies of bicycling safety.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0080) [Injury Prev. 17, e6–e6](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0080).

[Huang, H., Abdel-Aty, M.A., Darwiche, A.L., 2010. County-level crash risk analysis in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0085) [Florida. Transport. Res. Record: J. Transport. Res. Board 2148, 27–37](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0085).

*P. Chen / Safety Science 79 (2015) 336–343* 343

[Kim, J.-K., Kim, S., Ulfarsson, G.F., Porrello, L.A., 2007. Bicyclist injury severities in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0090) [bicycle-motor vehicle accidents. Accid. Anal. Prev. 39, 238–251](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0090).

[Klop, J.R., Khattak, A.J., 1999. Factors inﬂuencing bicycle crash severity on two-lane,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0095) [undivided roadways in North Carolina. Transport. Res. Record: J. Transport. Res.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0095) [Board 1674, 78–85](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0095).

[Knorr-Held, L., Besag, J., 1998. Modelling risk from a disease in time and space. Stat.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0100)

[Med. 17, 2045–2060](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0100).

[Lord, D., Mannering, F., 2010. The statistical analysis of crash-frequency data: a](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0105) [review and assessment of methodological alternatives. Transport. Res. Part A:](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0105) [Policy Practice 44, 291–305](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0105).

[Lusk, A.C., Furth, P.G., Morency, P., Miranda-Moreno, L.F., Willett, W.C., Dennerlein,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0110) [J.T., 2013. Risk of injury for bicycling on cycle tracks versus in the street. Injury](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0110) [Prev. 17, 131–135](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0110).

[Mannering, F.L., Bhat, C.R., 2014. Analytic methods in accident research:](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0115) [methodological frontier and future directions. Anal. Methods Accid. Res. 1,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0115) [1–22](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0115).

[Miranda-Moreno, L.F., Morency, P., El-Geneidy, A.M., 2011a. The link between built](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0120) [environment, pedestrian activity and pedestrian-vehicle collision occurrence at](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0120) [signalized intersections. Accid. Anal. Prev. 43, 1624–1634](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0120).

[Miranda-Moreno, L.F., Strauss, J., Morency, P., 2011b. Disaggregate exposure](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0125) [measures and injury frequency models of cyclist safety at signalized](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0125) [intersections. Transport. Res. Record: J. Transport. Res. Board 2236, 74–82](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0125).

[Narayanamoorthy, S., Paleti, R., Bhat, C.R., 2013. On accommodating spatial](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0130) [dependence in bicycle and pedestrian injury counts by severity level.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0130) [Transport. Res. Part B: Methodol. 55, 245–264](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0130).

[Park, E.S., Lord, D., 2007. Multivariate Poisson-lognormal models for jointly](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0135) [modeling crash frequency by severity. Transport. Res. Record: J. Transport.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0135) [Res. Board 2019, 1–6](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0135).

Puget Sound Regional Council, 2014. Activity-Based Travel Model: SoundCast.

<<http://www.psrc.org/data/models/abmodel/>>.

[Reynolds, C., Harris, M.A., Teschke, K., Cripton, P.A., Winters, M., 2009. The impact of](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0145) [transportation infrastructure on bicycling injuries and crashes: a review of the](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0145) [literature. Environ. Health 8, 47](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0145).

[Sakshaug, L., Laureshyn, A., Svensson, Å., Hydén, C., 2010. Cyclists in roundabouts-](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0150) [Different design solutions. Accid. Anal. Prev. 42, 1338–1351](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0150).

[Schepers, J., Kroeze, P., Sweers, W., Wüst, J., 2011. Road factors and bicycle-motor](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0155) [vehicle crashes at unsignalized priority intersections. Accid. Anal. Prev. 43,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0155) [853–861](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0155).

[Schepers, P., Hagenzieker, M., Methorst, R., van Wee, B., Wegman, F., 2013. A](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0160) [conceptual framework for road safety and mobility applied to cycling safety.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0160) [Accid. Anal. Prev.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0160)

[Siddiqui, C., Abdel-Aty, M., Choi, K., 2012. Macroscopic spatial analysis of pedestrian](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0165) [and bicycle crashes. Accid. Anal. Prev. 45, 382–391](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0165).

[Strauss, J., Miranda-Moreno, L.F., Morency, P., 2013. Cyclist activity and injury risk](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0170) [analysis at signalized intersections: a Bayesian modelling approach. Accid. Anal.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0170) [Prev. 59, 9–17](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0170).

[Teschke, K., Harris, M.A., Reynolds, C.C., Winters, M., Babul, S., Chipman, M.,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0175) [Cusimano, M.D., Brubacher, J.R., Hunte, G., Friedman, S.M., 2012. Route](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0175) [infrastructure and the risk of injuries to bicyclists: a case-crossover study.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0175) [Am. J. Public Health 102, 2336–2343](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0175).

The National Highway Trafﬁc Safety Administration, 2012. Trafﬁc safety facts: Bicyclists and other cyclists. <[http://www-nrd.nhtsa.dot.gov/Pubs/812018.](http://www-nrd.nhtsa.dot.gov/Pubs/812018.pdf) [pdf](http://www-nrd.nhtsa.dot.gov/Pubs/812018.pdf)>.

Tingvall, C., Haworth, N., 2000. Vision Zero: an ethical approach to safety and mobility. In: 6th ITE International Conference Road Safety & Trafﬁc Enforcement: Beyond.

U.S. Department of Transportation, 2009. National Household Travel Survey.

[Ukkusuri, S., Miranda-Moreno, L.F., Ramadurai, G., Isa-Tavarez, J., 2012. The role of](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0195) [built environment on pedestrian crash frequency. Saf. Sci. 50, 1141–1151](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0195).

[Vandenbulcke, G., Thomas, I., Int Panis, L., 2014. Predicting cycling accident risk in](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0200) [Brussels: a spatial case-control approach. Accid. Anal. Prev.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0200)

[Walker, I., 2007. Drivers overtaking bicyclists: objective data on the effects of riding](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0205) [position, helmet use, vehicle type and apparent gender. Accid. Anal. Prev. 39,](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0205) [417–425](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0205).

[Wang, Y., Kockelman, K.M., 2013. A Poisson-lognormal conditional-autoregressive](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0210) [model for multivariate spatial analysis of pedestrian crash counts across](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0210) [neighborhoods. Accid. Anal. Prev. 60, 71–84](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0210).

[Wang, Y., Nihan, N.L., 2004. Estimating the risk of collisions between bicycles and](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0215) [motor vehicles at signalized intersections. Accid. Anal. Prev. 36, 313–321](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0215).

Wegman, F., Dijkstra, A., Schermers, G., van Vliet, P., 2005. Sustainable Safety in the Netherlands: the vision, the implementation and the safety effects. In: Proceedings of the 3rd International Symposium on Highway Geometric Design. Chicago.

[Wegman, F., Zhang, F., Dijkstra, A., 2012. How to make more cycling good for road](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0225) [safety? Accid. Anal. Prev. 44, 19–29](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0225).

[Wei, F., Lovegrove, G., 2012. An empirical tool to evaluate the safety of cyclists:](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0230) [community based, macro-level collision prediction models using negative](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0230) [binomial regression. Accid. Anal. Prev.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0230)

[Zahabi, S.A.H., Strauss, J., Manaugh, K., Miranda-Moreno, L.F., 2011. Estimating](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0235) [potential effect of speed limits, built environment, and other factors on severity](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0235) [of pedestrian and cyclist injuries in crashes. Transport. Res. Record: J. Transport.](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0235) [Res. Board 2247, 81–90](http://refhub.elsevier.com/S0925-7535(15)00158-7/h0235).