FORECASTING BICYCLING RISK FACTORS WITHIN NEIGHBORHOODS: A SPATIAL AUTOREGRESSIVE APPROACH

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1. INTRODUCTION

In the United States transportation planning has predominantly consisted of designing roadways to move automobiles as efficiently as possible. As a result, planning for the automobile has resulted in environmental degradation, fragmented neighborhoods, and decreased public health (Newman Kenworthy, 1999). Alternative modes of transportation such as bicycling are viewed as means to counter these effects. However, safety concerns preclude most people from utilizing this transportation mode, especially for children (Sonkin, 2006; Heinen, 2010). This observation is evidenced when one considers that in 2003, 46,000 persons in the U.S. were involved in bicycle related injuries and a large amount of accidents go unreported every year (NCSA, 2003; Carter, 2007). While U.S. federal acts such as the Intermodal Surface Transportation Efficiency Act (ISTEA) and the Transportation Equity Act (TEA-21) has significantly transformed transportation policy in the U.S. to promote and encourage bicycling, efforts to increase bicyclist safety remain a top priority in elevating levels of bicycling (Vandenbulcke *et al.*, 2009).

2. BACKGROUND

The impetus for bicycle planning is to create an environment that is safe and attractive for current and potential bicyclists. Two primary means to accomplish this is through the creation of safety indices that quantify “comfort level” of bicyclists. Studies such as this focus on road intersections (Epperson, 1994; Landis, 2003; Wang, 2004; Carter, 2007), road segments (Landis *et al.*, 1997; Harkey *et al.*, 1998; Moore *et al.*, 2011), or city-wide bicycling infrastructure conditions (Clarke, 1992; Loo and Tsui, 2010). Invariably this research assimilates speed limits, traffic conditions, road classification, pavement conditions, or qualitative ratings of the environment into a safety index. Two popular segment based bicycle safety indices include Harkey’s (1998) Bicycle Compatibility Index (BCI) and the Bicycle Level of Service (BLOS) developed by Landis et al. (1997). Intersection specific indices have also been developed due to the high propensity for bicycle crashes at these locations (Wang, 2004). An example for this includes the intersection hazard score developed by Landis et al. (2003). In contrast to developing indices that measure bicyclist comfort, many studies utilize bicycle crash data directly at the micro or macro scale (Siddiqui *et al.*, 2011).

During the last two decades bicycle crash research has focused on utilizing bicycle crash accident data and have found that bicyclist age (Stone, 2003) bicyclist gender (Eilert-Petersson, 1997), alcohol expenditure per capita (Noland Quddus, 2004), neighborhood income (Epperson, 1995), population density (Vandenbulcke et al., 2009), traffic speed (Kim *et al.*, 2006), traffic rates (Mitra, 2007), roadway type (Reynolds *et al.*, 2009), intersection characteristics (Doherty, 2000), and land use types (Mitra, 2007) contribute to elevated bicycling danger levels. These studies typically derive crash risk correlates at the micro scale. Many of these studies also integrate qualitative surveys to determine how bicyclists rate various safety conditions. However, very few bicycle crash risk examinations assess the effects of area-wide ecological properties on bicycle crash rates, and an even smaller fraction of this research accounts for the spatial autocorrelation of bicycle crash rates or spatially aggregated data used to determine them (Siddiqui *et al.*, 2011).

Bicycling risk is a spatial phenomenon, and therefore, demands unique attention (Loo Tsui, 2010). A minimal amount of bicycle crash research accounts for spatial effects associated with spatially aggregated data. However, recent bicycle crash studies have begun to acknowledge the spatial properties of bicycle crash rates and associated spatial data. For example, Delmelle et al., (2012) studied adult and youth pedestrian and bicyclist risk factors such as, socio-demographic, street characteristics, economic conditions, and trip generation factors using a spatially weighted linear regression model. This study found that social, behavioral, and land use types within U.S. Census Tracts affect bicyclist and pedestrian crash rates. In addition, Siddequi et al., (2011) accounted for spatial affects by incorporating a Bayesian model that reviewed roadway, demographic, and socio-economic predicts of pedestrian and bicycle crashes within Traffic Analysis Zones (TAZ). To date there are no bicycle crash risk studies that emphasize on neighborhood characteristics. Determining causal bicycle risk factors within neighborhoods can provide stakeholders a broader comprehension of what factors contribute to increased bicyclist risk, resulting in a sound course of action to increase bicycling safety. Assessing bicycle crash risk at the neighborhood scale is a logical level of analysis for future policy action, enable a proactive strategy to identify problem areas, measure progress over time, and develop specific bicycle crash countermeasures that are aligned with current neighborhood planning strategies. In addition, identifying bicycle risk factors within neighborhoods is aligned with planning strategies that seek to increase neighborhood vitality, residential health, transportation access, mobility, and general neighborhood attractiveness (Frank *et al.*, 2003). Therefore, the objectives of this research are to; 1) identify possible contextual and socio-economic neighborhood factors causing spatial clustering of crash densities, 2) propose a methodology utilizing GIS and a spatial auto-regression (SAR) forecasting model that accounts for spatial effects and determine significant bicycling crash risk factors within neighborhoods.

3. DATA AND STUDY AREA

The study area and unit of analysis consists of the City of Milwaukee, Wisconsin and its 190 distinct neighborhoods (Fig 1). A legacy of neighborhood planning exists in Milwaukee, and therefore, utilizing neighborhood polygons in this study follows this trend and also fills a void in neighborhood analysis concerning bicycling risk (Ghose Huxhold, 2002). The neighborhood boundaries were obtained from the City of Milwaukee's GIS and Planning department in a GIS format.

FIGURE 1
CITY OF MILWAUKEE, WI AND NEIGHBORHOODS

The explanatory variables used in this study are partitioned into three groups: 1) socio-economic, 2) environment, and 3) transportation. They are summarized in table 1. To remain congruent to previous bicycle research socio-economic factors such as gender, race, age, income, and household characteristics were obtained from the 2000 U.S. Census SF-1 data files and included in this research. Adolescent and older adult age groups were analyzed separately for this research because these two groups are most susceptible to bicycling risk (Delmelle Thill, 2008). Environmental information was obtained from City of Milwaukee's 2006 Property file (MPROP) and includes building occupancy type, building characteristics, property size, and land use. In addition, public K-12 schools was obtained from the city of Milwaukee County Parks Department and utilized in this study to remain in line with previous bicycle crash risk analysis concerning school zones and school aged children (LaScala, 2004; Kim et al., 2006). Business data consisted of gasoline/convenience stores and was obtained from the City of Milwaukee and selected via the federal Standard Industrial Classification code. This dataset serves as a supplemental auto-orientated commercial land-use variable. Transportation and roadway data was obtained from the City of Milwaukee Engineering Department and the Wisconsin Department of Transportation (WIDOT) and consisted of traffic control type, roadway speed, pavement quality, traffic counts, roadway type, and pavement quality. Vehicle miles traveled (VMT) was derived to acknowledge automobile traffic intensity and economic conditions in each neighborhood. VMT per neighborhood was calculated using this equation: total AADT * 365 days/year * roadway length (ft) / 5280 ft. (per mile). The type of traffic control device is an important predictor of school-aged bicycle crashes, thus it was included in this study (Abdel-Aty et al., 2007). Bus routes were obtained from the Milwaukee County Transit Service (MCTS) to determine mass transit accessibility and neighborhood mobility options. To assess the existing safety of bicycling in each area, a bicycle level of service (BLOS), developed by Landis (1997), was computed for each neighborhood using several roadway factors and the mean was assigned to each neighborhood unit. Bicycle facility information, such as bike routes and lanes, was received from the Bicycle Federation of Wisconsin in a GIS format and used to represent the intensity of bicycle facilities present within each neighborhood. All independent variables were aggregated to the neighborhood, requiring the need for spatial analysis models that test for spatial autocorrelation.

The dependent variable in this study consists of bicycle collisions that involved motor vehicles, pedestrians, or other bicyclists from 1999 through 2003. Multiple years of crash data were utilized to increase model validity and overcome the regression-to-mean problem (Loo Tsui, 2010). Accidents that involved a reported injury or damage greater than \$500 were recorded using the Wisconsin Motor Vehicle Accident Report Form MV-4000. A total of 979 bicycle reported accidents were collected the Wisconsin Department of Transportation (WIDOT) within the specified time period. The bicycle accident database included incident address, manner of collision, number of injured, accident time, light conditions, road conditions.

4. RESEARCH METHODS

4.1 EXPLORATORY SPATIAL DATA ANALYSIS

Prior to conducting exploratory spatial data analysis (ESDA), all bicycle accidents in the study area were first geocoded and mapped using Environmental Systems Research Institute's (ESRI) ArcInfo 9.1. A bicycle accident density per neighborhood resulted by dividing the number of bicycle crash incident points per polygon area. This normalization was utilized to remove neighborhood size heterogeneity and to limits the randomness associated with single crash events, thus making any explanatory factors relevant to groups of accidents. The datasets used in this analysis originated from differing scales and differing geographic units, however, maximum attention to the modifiable areal unit problem (MAUP) was given in order to minimize model misspecification errors. Explanatory variables were aggregated per neighborhood and detailed in table 1.

TABLE 1
NEIGHBORHOOD FACTORS

Variable Name	Description
Socio-economic	
White	White population (percent)
Black	African American population (percent)
Male	Male population (percent)
Female	Female population (percent)
Pop < 5	Population (percent), age group under 5
Pop 5-17	Population (percent), age group 5 to 17
Pop 17-65	Population (percentage), age group 17 to 65
Household Income	Median household income
Household Size	Mean household size
Environmental Features	
Owner Occupied	Sum of owner occupied dwellings
Renter Occupied	Sum of renter occupied dwellings
Number of Stories	Mean number of building stories
Building Area	Mean total useable floor area (sq.ft.)
Lot Area	Mean property area (sq. ft.)
Land Use Types	Sum of different land-uses
Schools	Sum of schools
Commercial Land Use	Sum of commercial and gas stations
Gas Stations and Convenience Stores	Sum of gas station/convenience stores
Transportation Features	
Roadway	Mean # Roadway lanes
Interstate	Sum Interstate miles
Controlled Intersection	Sum controlled intersections
Uncontrolled Intersection	Sum uncontrolled intersections
Length of Bicycle Facilities	Sum miles of bicycle lanes/routes
Bicycle Level of Service (BLOS)	Mean BLOS
Pavement Quality	Mean pavement rating
Heavy Truck Traffic	Percent heavy vehicle traffic
Vehicle Miles Traveled (VMT)	Sum of Annual Vehicles Miles Traveled
Bus Routes	Sum bus routes miles

To test for spatial heterogeneity among neighborhood bicycle crash densities, a local indicator of spatial association (LISA) was conducted using GeoDa version 0.9.5 software. The aim of this procedure was to verify the presence of localized spatial groupings of neighborhood crash densities and is a necessary step prior to causal model development. A local Moran's I statistic was conducted to determine spatial clusters of low and high neighborhood bicycle crash densities. The Moran's I index is a valid local association index due to its common application in identifying vehicle crash "black spots," general ease of use, and stable results (Black, 1991; O'Sullivan, 2003). A 1st order rooks contiguity spatial weights matrix was used to account for shared geographic boundaries among neighborhoods- a typical means to delineate neighborhoods (Anselin, 2003b). Contiguity based weighting techniques assign weights based on the number of common boundaries (Anselin, 2003a).

4.2 BICYCLE CRASH RISK MODEL DEVELOPMENT

To explore causal relationships between neighborhood bicycle crash densities and explanatory factors, correlation analysis, ordinary least squares model, and a spatial auto regression model were implemented. A correlation analysis was first conducted in SPSS 16.0 (SPSS Inc. Chicago, IL, USA) to test the independent variables for statistical significance and colinearity. Important explanatory variables were retained for further model development based on their significant associations to the dependent variable and low colinearity with other predictors.

An identification of causal relationships between neighborhood bicycle crash densities and response variables was determined via a classical linear regression model and a spatial regression model using GeoDa version 0.9.5 software. The purpose of invoking a standard ordinary least squares (OLS) regression and a spatial auto-regression (SAR) model is to compare, contrast, and validate the use of a spatially explicit model. Spatial regression models accomplish this task by including a spatial autoregressive term that incorporates spatial locations directly into the equation via a neighborhood proximity matrix (Gamerman, 2004). Through tests of significance between a spatial error and spatial lag regression, the spatial lag SAR model was implemented in this research. The spatial lag regression model accounts for spatial dependency through a linear relation between the response variable and a spatially lagged variable using a maximum likelihood estimator (Fotheringham Rogerson, 1994). In essence, the spatial lag SAR model removes spatial clustering of the dependent variable (Levine, 1995).

The spatial lag SAR model is specified as:

$$y = pWy + X\beta + \varepsilon$$

Wy is the spatially lagged variable for weights matrix W
y is an N by 1 vector of observations on the dependent variable
X is an N by K matrix of observations on the explanatory variables
ε is an N by 1 vector of error terms
ρ is the spatial autoregressive parameter,
β is a K by 1 vector of regression coefficients

5. RESULTS

5.1 NEIGHBORHOOD CLUSTER ANALYSIS

The LISA analysis indicates that bicycle crash density per neighborhood is spatially autocorrelated as evidenced by a Moran's I index of 0.48 at the .05 significance level. This result falsifies the null hypothesis that neighborhood crash density is random. A LISA cluster map ($p < .05$) verifies that there is neighborhood bicycling crash density concentrations throughout the study area (Fig 2). Specifically, Figure 2 indicates that low crash densities (low-low) are apparent in the far northwest and southeast neighborhoods and elevated (high-high) densities are present in the central city neighborhoods. The elevated crash densities are located in areas that contain high population densities and moderate-low incomes. Low neighborhood crash densities are spatially correlated in suburban portions of the city that contain moderate incomes. We can infer from this analysis that location specific causes are influencing both low and high bicycle crash densities. More importantly, this result warrants the need to account for spatiality in the bicycle crash model.

5.2 REGRESSION VERSUS SPATIAL REGRESSION RESULTS

The initial OLS regression model was tested to serve as a baseline analysis for subsequent spatial regression model assessment. The results of both models are displayed in table 3. The R-squared for both the OLS and SAR models indicate moderate success in predicting neighborhood bicycling crash densities with selected explanatory variables. The SAR R-squared increased 11 percent when compared to the OLS result. However, the SAR R-squared is a pseudo coefficient and is not directly comparable to the OLS R-squared (Anselin, 2005). The Log likelihood coefficient, Schwarz criterion, and Akaike info criterion are based on the multivariate normality assumption and are comparable between the SAR and the OLS regression model (Anselin, 2005). The SAR log likelihood coefficient is greater than that of the OLS output, indicating a stronger model SAR performance The SAR Schwarz criterion coefficient and Akaike info criterion coefficient decrease relative to the OLS coefficients, providing additional empirical evidence that the SAR model is an improvement in modeling power over the traditional OLS model. The spatial lag SAR model is justified and lends credence to pertinent explanatory predictors

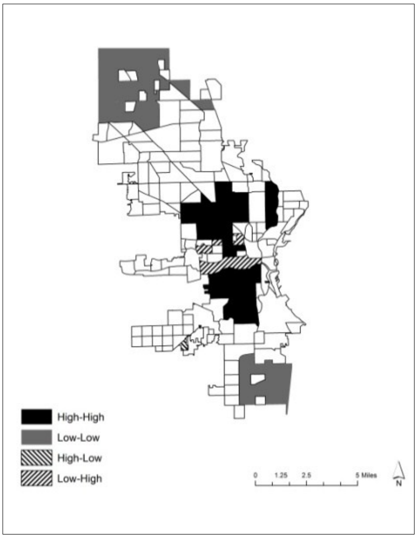

FIGURE 2
SPATIAL AUTOCORRELATION OF NEIGHBORHOOD BICYCLE CRASH DENSITIES

TABLE 3
SPATIAL LAG MODEL AND OLS MODEL COMPARISON

	Spatial Auto-Regression	Ordinary Least Squares
R-squared	.62	.51
Log likelihood	-677.22	-695.23
Schwarz criterion	1459.38	1490.17
Akaike info criterion	1394.44	1428.48

5.3 BICYCLIST CRASH MODEL ESTIMATES

The explanatory variables that are depicted in table 4 reveal the final set of 19 factors that were significantly correlated to the dependent variable and theoretically significant in this research. The SAR model results indicate that the predictors from the socio-economic and environmental groupings show significant causal relationships to bicycle crash density. These predictors include; sum gas station/stores, average household size, percent female, sum owner occupied housing, sum renter occupied housing, and average building stories per neighborhood are significant in this model. From these variables, summarized gas stations/stores, household size, renter occupied housing, and building height positively affect neighborhood bicycle crash densities ($p > .05$). These variables collectively represent neighborhoods that contain elevated commercial development, rental housing, and population density. Average household size exhibits the largest positive influence on neighborhood bicycle crash density. This relationship has been witnessed in other studies such as Delmelle *et al.*, (2012). The summation of total renter occupied housing is also significant and positively related to crash density. It can be inferred from this finding that neighborhoods that contain a large portion of renter occupied, or multi-family housing may represent persons with reduced incomes, resultantly; this may reflect a larger reliance on the bicycle for transportation than their homeowner counterparts, increasing their risk exposure (Epperson, 1995; Moudon *et al.*, 2005; Siddiqui et al., 2011; Delmelle *et al.*, 2012). Furthermore, the positive relationship between renter-occupied housing and bicycle crashes can also be attributed to the predominance of bicycle mode choice in areas with high population density. This finding is also supported by the negative influence of owner-occupied housing and bicycling crash densities witnessed in table 4. The density of gasoline/stores is also significantly related to increased bicycling risk density. The positive relationship corroborates previous research that points to a positive link between children bicyclists use and the location of commercial establishments such as this (Kraus, 1996). Furthermore, this outcome exhibited in Table 3 substantiates previous research and indicates that increased bicycling rates within neighborhoods increases risk exposure. The average number of stories of all buildings in each neighborhood represents urban intensity and has a positive effect on bicycling crashes. This result counters past research that point to decreasing bicycling risk in urban areas. For example Vandenbulke *et al.*, (2009) posits that higher proportion of pedestrians, traffic calming devices, congestion, etc. results in elevated bicyclist safety. The result presented here alludes to inter-municipality conditions that are not bicycle friendly, necessitating the need for progressive bicycle policy and infrastructure implementation so as to increase bicyclist safety. The final statistically significant explanatory variable is the proportion of females within neighborhoods. This variable holds an inverse relationship to bicyclist crash density. We can deduce from this relationship that as the proportion of females increase in a neighborhood the crash rate diminishes pointing to past research that exhibits a large portion of bicycle accidents involve males (Rodgers, 1997).

6. CONCLUSION

The intent of this study was to provide stakeholders additional contextual neighborhood information to proactively increase bicyclist safety while accounting for spatial heterogeneity. As postulated by Delmelle *et al.*, (2012), neighborhoods with certain characteristics require specific attention and planning to elevate the security of bicycling and walking. This research has internalized this sentiment and reached the first objective by focusing on explicit neighborhood socio-economic, environmental, and transportation attributes. The utility of this approach lies in its coordination with many neighborhood planning goals.

The overarching message exhibited in this research is that bicycling crash risk contains a spatial dimension that few bicycle studies acknowledge. Therefore, this research reached the second objective by implementing a spatial regression model to determine bicycle crash causal factors. Spatial autocorrelation of bicycle crash densities was verified through a LISA cluster analysis map and local Moran's I statistic. A spatial lag SAR and OLS model was then implemented to assess the differences in performance between a traditional and spatially explicit model. In both cases, the SAR model exhibited increased robustness. Significant SAR causal factors ($p < .05$) include, gender, commercial land uses, household size, renter occupied housing, owner occupied housing, and building height. All but building height (urban intensity) displayed logical relationships to bicycle crash risk. Collectively however, the neighborhood components witnessed in this research represent areas that contain elevated bicycling activity and increased bicycling un-safety- providing stakeholders additional knowledge on where to focus bicycle safety measures. The current analysis did not incorporate direct bicyclist exposure, *i.e.*, bicycle count data, which is a known issue in many studies of this nature. Including direct bicyclist exposure data would substantiate this research and perhaps highlight other relevant causal factors, however, this data was not available at the time of this study.

TABLE 4
PREDICTORS OF NEIGHBORHOOD CRASH RATES IN THE SAR MODEL

Variable	Coefficient	Std. Error	z-value	Probability
Med HH Income	-9.408	8.094	-1.162	0.245
Sum Gas/Stores	2.314	0.816	2.833	0.004*
School Sum	0.031	0.394	0.080	0.935
Mean Pvt Cond.	2.725	3.427	0.795	0.426
Total VMT	1.600	3.750	0.425	0.670
Land-use Sum	0.037	0.107	0.352	0.724
Total Bus Rts	0.054	0.641	0.085	0.931
Controlled Inter	0.218	0.197	1.104	0.269
Ave HH Size	6.401	1.419	4.510	0.000*
Prop of White	-0.051	0.041	-1.252	0.210
Prop of Male	0.101	0.134	0.752	0.451
Prop of Female	-0.254	0.110	-2.308	0.020*
Age under 5	0.095	0.342	0.278	0.780
Age 5-17	-0.089	0.172	-0.521	0.602
Age 17-65	-0.023	0.096	-0.247	0.804
Sum OO	-0.005	0.001	-3.729	0.000*
Sum RO	0.002	0.001	2.409	0.015*
Ave Bldg Story	0.595	0.280	2.123	0.033*
Ave Lot Area	-6.180	8.340	-0.740	0.458
**significant at $p < .05$*				

7. REFERENCES

Abdel-Aty, M., S.S. Chundi, and C. Lee, 2007, Geo-Spatial and Log-Linear Analysis of Pedestrian and Bicyclist Crashes Involving School-Aged Children. *Journal of Safety Research,* 38(5), 571-579.

Anselin, L., 2005, Exploring Spatial Data with Geoda: A Workbook. Department of Agriculture and Consumer Economics, University of Illinois.

Anselin, L., 2003a, Geoda 0.9 a Users Guide. Department of Agricultural and Consumer Economics, University of Illinois, Urbana-Champaign.

Anselin, L., R. Bongiovanni, and J. Lowenberg-DeBoer, 2003b, A Spatial Econometric Approach to the Economics of Site-Specific Nitrogen Management in Corn Production. *American Journal of Agricultural Economics,* 86(3), 675-687.

Black, W.R., 1991, Highway Crashes: A Spatial and Temporal Analysis. *Transportation Research Record,* 1318 75-82.

Carter, D.L., W.W. Hunter, C.V. Zegeer, J.R. Stewart, and H. Huang 2007, Bicyclist Intersection Safety Index. *Transportation Research Record: Journal of the Transportation Research Board,* (2031), 18-24.
Clarke, A., 1992, Bicycle Friendly Cities: Key Ingredients for Success. *Transportation Research Record: Journal of the Transportation Research Board,* (1372), 71-75.
Delmelle, E.C., and J.C. Thill, 2008, Urban Bicyclists: Spatial Analysis of Adult and Youth Traffic Hazard Intensity. *Transportation Research Record: Journal of the Transportation Research Board,* 2074 31-39.
Delmelle, E.C., J.C. Thill, and H.H. Ha, 2012, Spatial Epidemiologic Analysis of Relative Collision Risk Factors among Urban Bicyclists and Pedestrians. *Transportation,* 1-16.
Doherty, S.T., L. Aultman-Hall, J. Swaynos, 2000, Commuter Cyclist Accident Patterns in Toronto and Ottawa. *Journal of Transportation Engineering,* 21-26.
Eilert-Petersson, E., L. Schelp, 1997, An Epidemiological Study of Bicycle-Related Injuries. *Accident Analysis & Prevention,* 29(3), 363-372.
Epperson, B., 1995, Demographic and Economic Charactersitics of Bicyclists Involved in Bicycle-Motor Vehicle Accidents. *Transportation Research Record: Journal of the Transportation Research Board,* (1502), 58-64.
Epperson, B., 1994, Evaluating Suitability for Roadways for Bicycle Use: Toward a Cycling Level-of-Service Standard. *Transportation Research Record: Journal of the Transportation Research Board,* (1438), 9-16.
Fotheringham, A.S., and P. Rogerson, 1994, *Spatial Analysis and GIS*. Taylor & Francis.
Frank, L.D., P.O. Engelke, and T.L. Schmid, 2003, *Health and Community Design: The Impact of the Built Environment on Physical Activity*. Island Pr.
Gamerman, D., and A. Moreira, 2004, Multivariate Spatial Regression Models. *Journal of Multivariate Analysis,* 91 262-281.
Ghose, R., and W. Huxhold, 2002, Role of Multi-Scalar GIS-Based Indicators Studies in Formulating Neighborhood Planning Policy. *Journal of Urban and Regional Information Systems Association,* 14(2), 5-17.
Harkey, D.L., D.W. Reinfurt, and M. Knuiman, 1998, Development of the Bicycle Compatibility Index. *Transportation Research Record: Journal of the Transportation Research Board,* 1636 13-20.
Heinen, E., B. Van Wee, K. Maat, 2010, Commuting by Bicycle: An Overview of the Literature. *Transport Reviews,* 30(1), 59-96.
Kim, J.K., S. Kim, G.F. Ulfarsson, and L.A. Porrello, 2006, Bicyclist Injury Severities in Bicycle-Motor Vehicle Accidents. *Accident Analysis & Prevention,* 39(2), 238-251.
Kraus, J.F., E.G. Hooten, K.A. Brown, C. Peek-Asa, C. Heye, D.L. McArther, 1996, Child Pedestrian and Bicyclist Injuries: Results of Community Surveillance and a Case-Control Study. *Injury Prevention,* 2 212-219.
Landis, B.W., V.R. Vattikuti, R.M. Ottenburg, T.A. Petritsch, M. Guttenplan, L.B. Crider, 2003, Intersection Level of Service for the Bicycle through Movement. *Transportation Research Record: Journal of the Transportation Research Board,* (1828), 101-106.
Landis, B.W., V.R. Vattikuti, and M.T. Brannick, 1997, Real-Time Human Perceptions: Toward a Bicycle Level of Service. *Transportation Research Record,* 1578(1997), 119-126.
LaScala, E., P. Greenwald, F. Johnson, 2004, An Ecological Study of the Locations of Schools and Child Pedestrian Injury Collisions. *Accident Analysis & Prevention,* 36 569-576.
Levine, N., K.E. Kim, L.H. Nitz, 1995, Spatial Analysis of Honolulu Motor Vehicle Crashes: Ii. Zonal Generators. *Accident Analysis & Prevention,* 27(5), 675-685.
Loo, B.P.Y., and K.L. Tsui, 2010, Bicycle Crash Casualties in a Highly Motorized City. *Accident Analysis & Prevention,* 42(6), 1902-1907.

Mitra, S., S.P. Washington, I. Schalkwyk. 2007. Important Omitted Spatial Variables in Safety Models: Understanding Contributing Crash Causes at Intersections, Transportation Research Board Annual Meeting, Washington D.C.,

Moore, D.N., W.H. Schneider Iv, P.T. Savolainen, and M. Farzaneh, 2011, Mixed Logit Analysis of Bicyclist Injury Severity Resulting from Motor Vehicle Crashes at Intersection and Non-Intersection Locations. *Accident Analysis & Prevention,* 43(3), 621-630.

Moudon, A.V., C. Lee, A.D. Cheadle, C.W. Collier, D. Johnson, T.L. Schmid, and R.D. Weather, 2005, Cycling and the Built Environment, a US Perspective. *Transportation Research Part D,* 10(3), 245-261.

NCSA. 2003. *Traffic Safety Facts, 2003 Data, Pedalcyclists*. U. S. D. o. Transportation. DOT HS 809 768

Newman, P., and J.R. Kenworthy, 1999, *Sustainability and Cities: Overcoming Automobile Dependence*. Island Press.

Noland, R.B., and M.A. Quddus, 2004, Analysis of Pedestrian and Bicycle Casualties with Regional Panel Data. *Transportation Research Record: Journal of the Transportation Research Board,* 1897(-1), 28-33.

O'Sullivan, D., Unwin, D.L., 2003, *Geographic Information Analysis*. Hoboken: John Wiley & Sons, Inc.

Reynolds, C.C.O., M.A. Harris, K. Teschke, P.A. Cripton, and M. Winters, 2009, The Impact of Transportation Infrastructure on Bicycling Injuries and Crashes: A Review of the Literature. *Environmental Health,* 8(1), 47.

Rodgers, G.B., 1997, Factors Associated with the Crash Risk of Adult Bicyclits. *Journal of Safety Research,* 28 233-241.

Siddiqui, C., M. Abdel-Aty, and K. Choi, 2011, Macroscopic Spatial Analysis of Pedestrian and Bicycle Crashes. *Accident Analysis & Prevention,* 45 382-391.

Sonkin, B., P. Edwards, I. Roberts, J. Green, 2006, Walking, Cycling and Transport Safety: An Analysis of Child Road Deaths. *Journal of the Royal Society of Medicine,* 99 402-405.

Stone, M., J. Broughton, 2003, Getting Off Your Bike: Cycling Accidents in Great Britain in 1990-1999. *Accident Analysis & Prevention,* 35(4), 549-556.

Vandenbulcke, G., I. Thomas, B. De Geus, B. Degraeuwe, R. Torfs, R. Meeusen, and L. Int Panis, 2009, Mapping Bicycle Use and the Risk of Accidents for Commuters Who Cycle to Work in Belgium. *Transport Policy,* 16(2), 77-87.

Wang, Y., N.L. Nihan, 2004, Estimating the Risk of Collisions between Bicycles and Motor Vehicles at Signalized Intersections. *Accident Analysis & Prevention,* 36 313-321.