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Bicyclist safety performance functions for a U.S. city

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ABSTRACT

Efforts have intensified to apply a more evidence-based approach to traffic safety. One such effort is the Highway Safety Manual, which provides typical safety performance functions (SPFs) for common road types. SPFs model the mathematical relationship between frequency of crashes and the most significant causal factors. Unfortunately, the manual provides no SPFs for bicyclists, despite disproportionately high fatalities among this group. In this paper, a method for creating city-specific, bicycle SPFs is presented and applied to Boulder, Colorado. This is the first time a bicycle SPF has been created for a U.S. city. Such functions provide a basis for both future investigations into safety treatment efficacy and for prioritizing intersections to better allocate scarce funds for bicycle safety improvements. As expected, the SPFs show that intersections with higher bicyclist traffic and higher motorist traffic have higher motorist-cyclist collisions. The SPFs also demonstrate that intersections with more cyclists have fewer collisions per cyclist, illustrating that cyclists are safer in numbers. Intersections with fewer than 200 entering cyclists have substantially more collisions per cyclist.

1. Introduction

Bicycle trips in the United States account for one percent of all trips and less than one percent of commuter mode shares, but with more than two percent of the total road deaths, cyclists appear to have disproportionately higher numbers of fatalities (U.S. Department of Transportation, 2009). Despite the road safety disadvantages, cycling does provide a physical activity, which has been shown to help prevent obesity and obesity related diseases (National Institutes of Health, 1998). Reducing hazards to cycling is a worthy goal.

Toward this goal, efforts are being made to map motorist-cyclist collisions and identify locations for future safety improvements. While the total number of collisions at a given location is important to identify, a better understanding of the underlying relationship between the number of collisions and the exposure to collisions – also known as safety performance functions (SPFs) – can provide the basis for a more effective method to prioritize intersections (Kononov and Allery, 2004). A misunderstanding of the true relationship between collisions and exposure to collisions often causes analysts to simply calculate the collisions per vehicle at each intersection by dividing the number of collisions by the volume of bicyclists or motor vehicles. Using this metric to compare intersections represents a fundamental misunderstanding and can produce misleading results, misappropriated funds, and unnecessary roadway hazards (Hauer, 1995).

Consequently, efforts have intensified to apply a more evidence-based approach to traffic safety in general. One such undertaking is the publication of the first Highway Safety Manual (HSM), which provides typical motor vehicle SPFs for common roadway types (American Association of State Highway and Transportation Officials, 2010). This manual provides an evidence-based method for estimating motor vehicle collisions based on SPFs developed from hundreds of intersections throughout the country; unfortunately, the methods for estimating bicyclist collisions are not nearly as well developed. Because bicycle volume data are rare, too few studies have created bicycle specific SPFs. The current recommendation is that predicted bicyclist collisions should be computed by multiplying the predicted number of motor vehicle collisions by a factor that is based upon motor vehicle speed and road type. While the number of motorist collisions, speed, and road type may be important factors in estimating the number of cyclist collisions, none of these are measures of cyclist exposure. Since SPFs commonly describe the relationship of collisions to exposure, cyclist exposure must be measured in order to create a bicycle-specific

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SPF. Several studies document the importance of bicyclist exposure in estimating the number of motorist-cyclist collisions by showing that the relationship between the number of bicycle-related collisions and bicyclist traffic volume is non-linear. This is often called the "safety in numbers" effect, since it has been found that collisions per cyclist tends to decrease with increasing cycling (Ekman, 1996; Leden et al., 2000; Jacobsen, 2003; Jonsson, 2005; Robinson, 2005).

This study presents a method for creating bicycle-specific SPFs similar to that used for motor vehicles in the HSM and applies that method to motorist-cyclist collisions at intersections in Boulder, Colorado. To the knowledge of the authors of this paper, these are the first such bicycle-specific SPFs developed for a city in the United States. Such studies have been listed as needed research by the Transportation Research Board Committee on the Operational Effects of Geometrics (Transportation Research Board, 2010). This work is an important first step toward fulfilling this need.

Better understanding the fundamental relationship of traffic volume to collisions will help lay the groundwork for future studies and allow cities to investigate the impact of specific infrastructure, speed, or other potential factors that may impact bicyclist safety. The focus of this study is not to create a definitive SPF for bicycles in the U.S., but to make a first step toward this end and initiate a discussion of what such a relationship is, why it is important, and what it can be used for. We achieve this by presenting a case study that highlights the benefits of a safety performance function approach to bicyclist safety.

2. Literature review

In the traffic safety community, the discussion of the relationship of traffic volume to safety has been enduring for decades (Smeed, 1949). Researchers have discovered that the relationship of traffic volumes to the number of collisions is non-linear, and that the shape of the curve is such that the number of collisions per vehicle decreases with increasing volumes, often referred to as the "safety in numbers" effect.

The HSM documents many SPFs for motor vehicles at intersections and road segments, most of which demonstrate that vehicular traffic can be "safer in numbers" (American Association of State Highway and Transportation Officials, 2010). These relationships are developed from crash data for hundreds of locations with similar characteristics. The manual documents how to predict crashes at similar intersections or road segments by using the SPF as a base and adjusting it with "crash modification factors" based on the specific geometrics or other features of the location. The manual also provides a basic method for predicting motorist-cyclist crashes by multiplying the total predicted motorist crashes by a factor based on speed and road type, but it does not account for cyclist volume whatsoever. A better method would include cyclist volume, but developing such a SPF for cyclists has certain challenges including: insufficient crash data; insufficient cyclist volume data; and a considerable range of facility types, many of which are scarce, such as cycle tracks or bicycle boulevards. While crashes are rare for motor-vehicles, low bicyclist mode share makes them even rarer for cyclists in the U.S., which in turn makes the development of cyclist specific SPFs even more challenging.

That similar non-linear relationships (i.e. "safety in numbers") hold for cyclists as well as other vehicle types (Hauer, 1995) is not all that surprising, but at the same time, it fundamentally invalidates longstanding conventional wisdom that the number of cyclist collisions should increase in direct proportion to the number of cyclists. The concept of safety performance functions can and should be applied to cyclist safety as well as motor-vehicle traffic.

In the mid-1990s, Swedish studies recorded some of the first bicycle SPFs for intersections, which showed that collisions and conflicts per cyclist decrease with increasing bicyclists (Brüde and Larsson, 1993; Ekman, 1996). Other researchers in Europe, Australia, New Zealand, and Canada have continued investigating this relationship, also finding that safety per bicyclist increases with increasing bicycle volumes (Leden et al., 2000; Jonsson, 2005; Robinson, 2005; Miranda-Moreno et al., 2011; Schepers et al., 2011; Turner et al., 2011b; Strauss et al., 2013). These studies are summarized by Elvik (2009) and generally assume a functional form for the SPF, usually a power function, and often focus on intersection collisions in cities because most cyclist-motor vehicle collisions in the urban environment occur at intersections (Hunter et al., 1996; Ferrara, 2001; Hamann and Peek-Asa, 2013).

In the U.S. and Europe, Jacobsen studied crashes at both the state and national levels, finding that crashes per cyclist decrease as overall cyclist mode shares increase (Jacobsen, 2003). However, bicycle safety performance functions for specific cities in the U.S. have not yet been developed. Jacobsen's study did not use bicycle count data. Such studies with sufficient detail are needed in order to evaluate the safety impact of bicycle safety remediation efforts, including infrastructure such as bicycle lanes and paths.

The literature has identified bicycle specific infrastructure, street lighting, and angle of grade as influencing cyclist safety (Reynolds et al., 2009), but without properly accounting for exposure, it is difficult to know if accurate comparisons are being made. This research endeavors to tackle this void in the literature in order to create the first bicycle-specific SPFs for a U.S. city.

3. Materials and methods

While this study does not investigate specific infrastructure types, it does develop bicyclist intersection safety performance functions – and a methodology for developing such – for one U.S. city, Boulder, Colorado. Boulder was chosen for study because it has one of the highest bicycle mode shares of any city in the U.S., at roughly 12 percent, as well as a history of counting bicycles using both manual counters and automated inductive-loop detectors (Lewin, 2005; U.S. Department of Commerce, 2009; City of Boulder, 2010; Nordback and Janson, 2010; Nordback et al., 2011). Boulder also has databases of bicycle and pedestrian collisions that can be used to examine intersection safety (Gill, 2007; City of Boulder, 2012). Thus, Boulder is one of the few cities in the U.S. with both sufficient bicycle volumes and collision data. Fortunately, technology for counting bicycles is becoming more common and more cities are collecting bicycle counts and crash data to make similar studies possible in the near future.

Intersections were the chosen unit of analysis since over two-thirds of the motorist-cyclist collisions in the Boulder datasets occurred at intersections or were intersection related. To quantify exposure at intersections, annual average daily traffic (AADT) and annual average daily bicyclists (AADB) were computed based on turning movement counts collected by the city of Boulder.

Bicyclist safety was modeled as the number of motorist-cyclist intersection collisions reported in police reports during the five year period from 2001 to 2005 and the four year period from 2008 to 2011 because these were the available datasets (Gill, 2007; City of Boulder, 2012). These collisions were aggregated by intersection; non-intersection crashes were excluded from the dataset used to develop the intersection SPF.

The SPF was modeled as a negative binomial model using a generalized linear model with log link, to help depict trends in the data. Once a SPF is chosen, it theoretically becomes possible to then predict the expected number of collisions at each intersection, given the traffic volumes present. The predicted number of collisions can then be compared to the observed number of collisions, and the relatively least safe intersections can be identified. Such an approach would allow the intersections to be best prioritized for remediation.

3.1. Data

Three types of data were used in this study: collision data, AADT, and AADB. Since AADB is not a readily available metric, two types of non-motorized traffic data were used to compute it: continuous bicycle count data and peak hour turning movement counts at each intersection studied. Each data source is discussed in further detail below.

Two motorist-cyclist collision databases are available for the city of Boulder. The first was provided by Jacobs Engineering under contract with the Colorado Department of Transportation (CDOT) and covers five years, 2001 through 2005 (Gill, 2007). The second was provided by the city of Boulder and covers four years, 2008 through 2011 (City of Boulder, 2012). Both of the databases were created using the Pedestrian and Bicycle Crash Analysis Tool (PBCAT) (Federal Highway Administration) and a geographic information system (GIS).

The collision data used in this study were obtained from police reports from the Boulder Police Department and were limited to collisions involving bicyclists at or near intersections. In the datasets, the majority of collisions involved an injury with just 17% of collisions in the earlier dataset and 15% in the later dataset recorded as non-injury. Almost all of the collisions in the datasets were motorist-cyclist collisions.

For the 2001–2005 dataset, 198 motorist-cyclist collisions at 105 signalized intersections were included in the study. For the 2008–2011 dataset, 285 motorist-cyclist collisions at 106 signalized intersections were studied (Fig. 1). While police-documented collisions miss many collision types, especially those with less than one thousand dollars in property damage and no documented injuries, they provide a useful measure of fatal and severe collisions between bicyclists and motor-vehicles.

A survey of bicyclists and pedestrians admitted to emergency rooms in New York, California, and North Carolina found that 70% of bicyclist injury events do not involve motorists and 31% of cyclist injury events were not on the roadway system (Stutts and Hunter, 1999). The authors also observe that the most severe cyclist injuries were usually in events involving motor vehicles. For the purposes of this study, minor collisions resulting in no harm or scrapes and bruises are of less interest than major collisions, which are more likely to result in long-term health problems. Though there are certainly many collisions that will not be captured in the crash reports included in the datasets used, crash reports provide a reasonable measure of fatal and severe collisions. The collisions studied here are mainly fatal and severe injury collisions, which may be representative of bicycle motor vehicle conflicts in general.

Fig. 2 shows how the number of motorist-cyclist collisions in each dataset varies by year, including collisions on road segments and those at both signalized and non-signalized intersections. The earlier dataset suggests a trend of decreasing motorist-cyclist collisions with time, while the newer data seem to show a slight increasing trend with time. Neither trend would account for the change in the magnitude of collisions between 2005 and 2008. For this reason and because the two collision datasets were created by different entities with different resources and interests, the magnitude of the collisions between the datasets should not be compared. The difference in magnitude between the two datasets could be due to changing criteria for writing police reports, changing information recorded in the reports, or greater thoroughness in collecting and assembling the second dataset.

Two measures of exposure of cyclists to collisions were used in this study: intersection AADB and intersection AADT. Those represent, respectively, the volume of bicyclists passing through the intersection and the volume of motorists passing through the intersection. Both were computed based on intersection turning movement counts collected by the city of Boulder for morning, noon, and evening peak hours at most signalized intersections in the city (City of Boulder, 2010).

For motorized traffic, the three peak hour counts were adjusted to daily counts using a factoring method provided by the city of Boulder (City of Boulder, 2010) (dividing the sum of three peak hour turning movement counts by 0.225). These estimates of daily counts were then multiplied by daily and monthly factors provided by CDOT for minor collector roads for the appropriate year to estimate AADT using the following equation from the Traffic Monitoring Guide (TMG) (Federal Highway Administration, 2013).

$$AADT_e = c_{kp} * D_{pyf} * M_{pyf} \tag{1}$$

where $AADT_e$ is the estimated annual average daily motorized traffic; c_{kp} is the (known count for sum of three peak hours (8,12,5) on a Tuesday, Wednesday, or Thursday (TWorR))/0.225; D_{pyf} is the daily motor vehicle factor for a given month in a given year y for a factor group f for TWorR and M_{pyf} is the monthly factor for a given month in a given year y for a factor group f.

For bicyclist traffic, two methods were used to estimate AADB from the turning movement counts: a factor method similar to that used for motorists and a statistical model dependent upon time, weather, and one spatial variable (Nordback, 2012). The factor method involved computing monthly and daily factors for each year studied to adjust for variation by season and day of week. These factors were computed based on continuous bicycle counts provided by the city of Boulder using methods similar to that recommended for motorized traffic in the Traffic Monitoring Guide (Federal Highway Administration, 2001). The basic equation for this method is given below:

$$AADB_e = c_{kp} * D_{pyf} * M_{pyf} \tag{2}$$

where $AADB_e$ is the estimated annual average daily bicyclists; c_{kp} is the known count for sum of three peak hours (8,12,5) on a TWorR; D_{pyf} is the factor for a given month in a given year y for a factor group f for all Tuesdays, Wednesdays and Thursdays (TWR) for the sum of the three peak hour counts and (average daily count for TWR only for a given month in a given year)/(average three peak hour count per day for TWR only for a given month and year); M_{pyf} is the monthly factor for a given month in a given year y for a factor group f and (actual AADB for that year)/(average daily count for TWR only for a given month in a given year).

The statistical model was a negative binomial model of exponential form with variables including month, year, day of the week, time of day, workday or not, university school day or not, whether a commute pattern was observed or not, and hourly temperature (Nordback, 2012). The basic equations for the statistical model used to compute AADB are shown below (see Nordback, 2012, for values of a, b, c, m_i, $CompDat2_j$, h and k):

$$c_{eh} = e^{a+bT+cT^2+m_i+CompDat2_j+hS+kD} \tag{3}$$

where c_{eh} is the estimated hourly count; a is the intercept parameter; b and c are model estimated parameters for the variable hourly temperature; T is average hourly temperature; m_i is a model estimated parameter for a given month; $CompDat2_j$ is a model estimated parameter for a given year, whether the day is a work day or not, and hour of the day; h and k are model estimated parameters for solar radiation and school day respectively. S is the hourly solar radiation measured in watts/meter^2; D is a dummy variable which

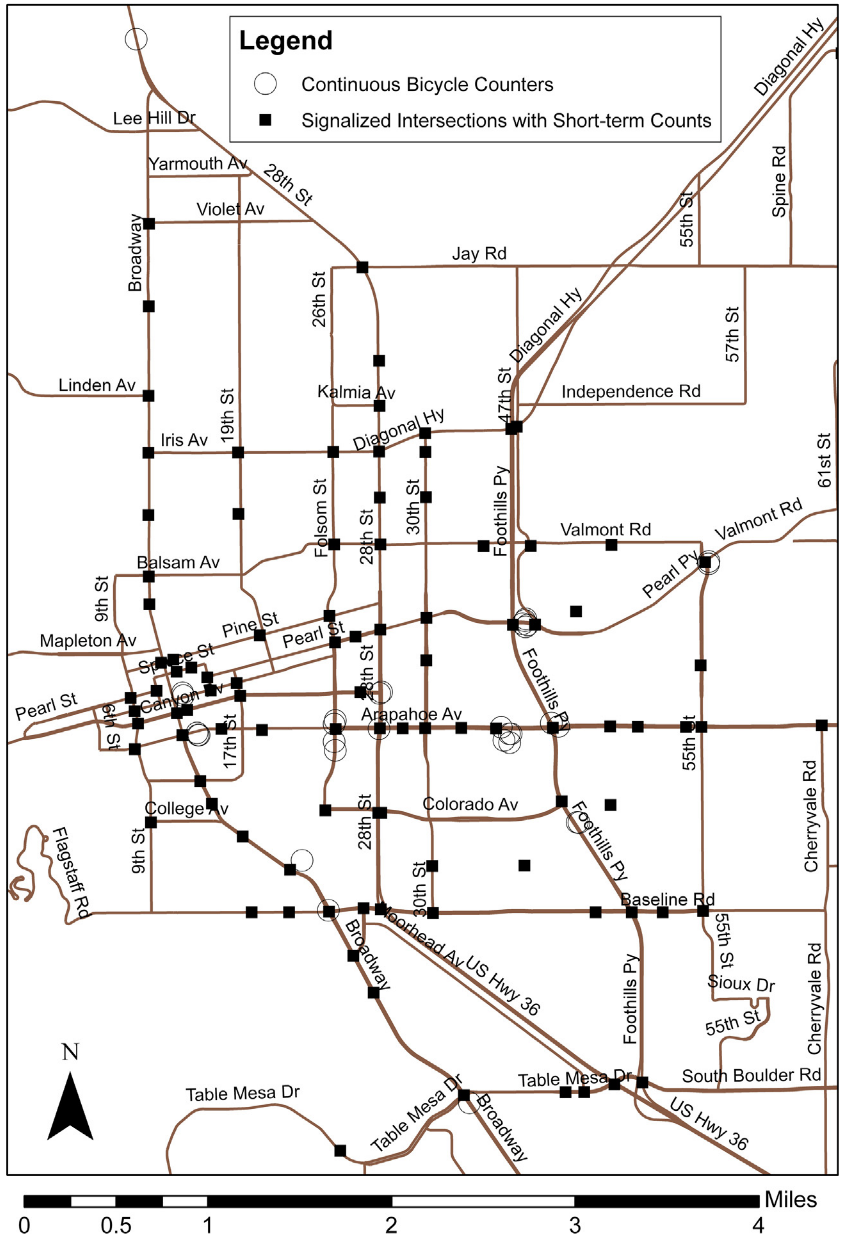

Fig. 1. Continuous bicycle count stations and signalized intersections in the city of Boulder.

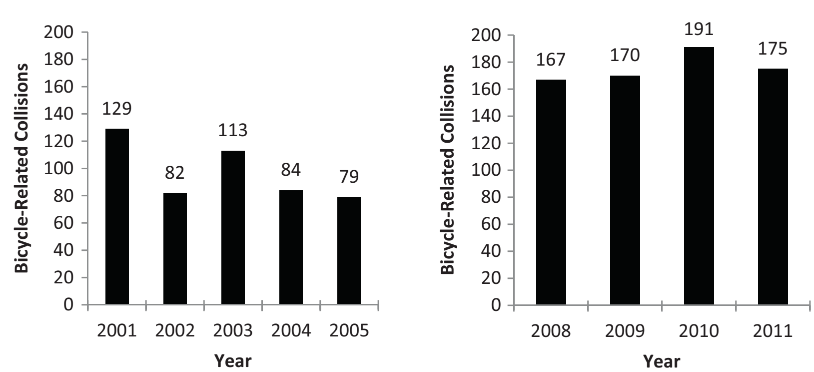

Fig. 2. Motorist-cyclist collisions by year at all intersections.

is one for University of Colorado Boulder spring or fall semester school days, and zero for all other days.

$$AADB_e = \left(\frac{c_{kp}}{c_{ep}}\right) * \frac{\Sigma^{year} c_{eh}}{365} \quad (4)$$

where $AADB_e$ is the estimated annual average daily bicyclists; c_{kp} is the known count for time period p; c_{ep} is the estimated count from statistical model for time period $p = \sum^{p} c_{eh}$.

Both the factor and statistical methods were created using a dataset from 26 continuous automated inductive-loop bicycle count stations located at twelve locations throughout the city as shown in Fig. 1. Three of the stations are on-street, and the rest are on multi-use paths. For a full explanation of the methods, see Nordback, 2012. Average absolute percent error of AADB estimates compared to actual AADB using the factor method varied from 30% to 47% across the four locations studied and averaged 40% (Nordback et al., 2014 Forthcoming). The average absolute percent error of the AADB estimates when compared to actual AADB using the statistical model ranged from 23% to 46% across the four locations studied and averaged 38% (Nordback, 2012). When both methods could be used, the average of the two estimates was used as the AADB estimate. Analysis of the AADB estimation error found that error varied substantially by month with the highest error in winter months when counts were lowest and most variable and the lowest error in the summer months (Nordback et al., 2014 Forthcoming). While the average absolute percent error in AADB estimation of 38% to 40% may appear high, most studies of bicyclist safety, which include any estimate of bicyclist volume, use short duration counts without attempting to annualize these counts, resulting in unknown and unreported error. For this reason, the analysis provided herein represents a step forward in understanding cyclist safety.

AADT and AADB, for both datasets, were adjusted using annual growth factors. For the earlier dataset, intersection volumes were adjusted to the year 2003, while for the later dataset, the volumes were adjusted to 2010. The annual growth factors for AADT were based on CDOT AADT estimates at 64 locations in the city of Boulder from 2001 to 2010; for AADB, growth factors were computed from the continuous bicycle count data. Growth factors are computed by dividing the known AADT (or AADB in this case) for a given year by the known AADT (or AADB) for the year of interest, in this case, 2003 or 2010. Full details of the AADB and AADT estimation methods can be found in a recent publication (Nordback, 2012). All signalized intersections for which intersection AADB and AADT could be calculated were included in the study.

3.2. Methods

For this analysis, a functional form that best fits the data was chosen to show the basic trend of the relationship of bicycle and motor vehicle traffic to motorist-cyclist collisions. Since collisions are discrete variables, the Poisson distribution could be a logical fit for the data. However, the variance of the collision data collected for both datasets is roughly triple the mean, which indicates that the collision data are overdispersed (American Association of State Highway and Transportation Officials, 2010). Thus, the Poisson distribution, for which the mean equals the variance, is not the best model for these data (Lord and Mannering, 2010). The overdispersion is likely due to the error in AADB estimation and the heterogenous nature of this dataset, which includes a diverse spectrum of signalized intersection types. The collisions are distributed by number of intersections as shown in Fig. 3.

Collision data are often found to be overdispersed, and commonly, the negative binomial model is employed to handle such situations (Turner et al., 2006). The model accounts for overdispersion by introducing a stochastic component to the log-linear Poisson mean function relationship (Long, 1997; Marshall and Garrick, 2011). Accordingly, a negative binomial generalized linear model was chosen to estimate the SPF. This matches the general shape observed from the non-parametric analysis using a 20-point moving average (Fig. 4).

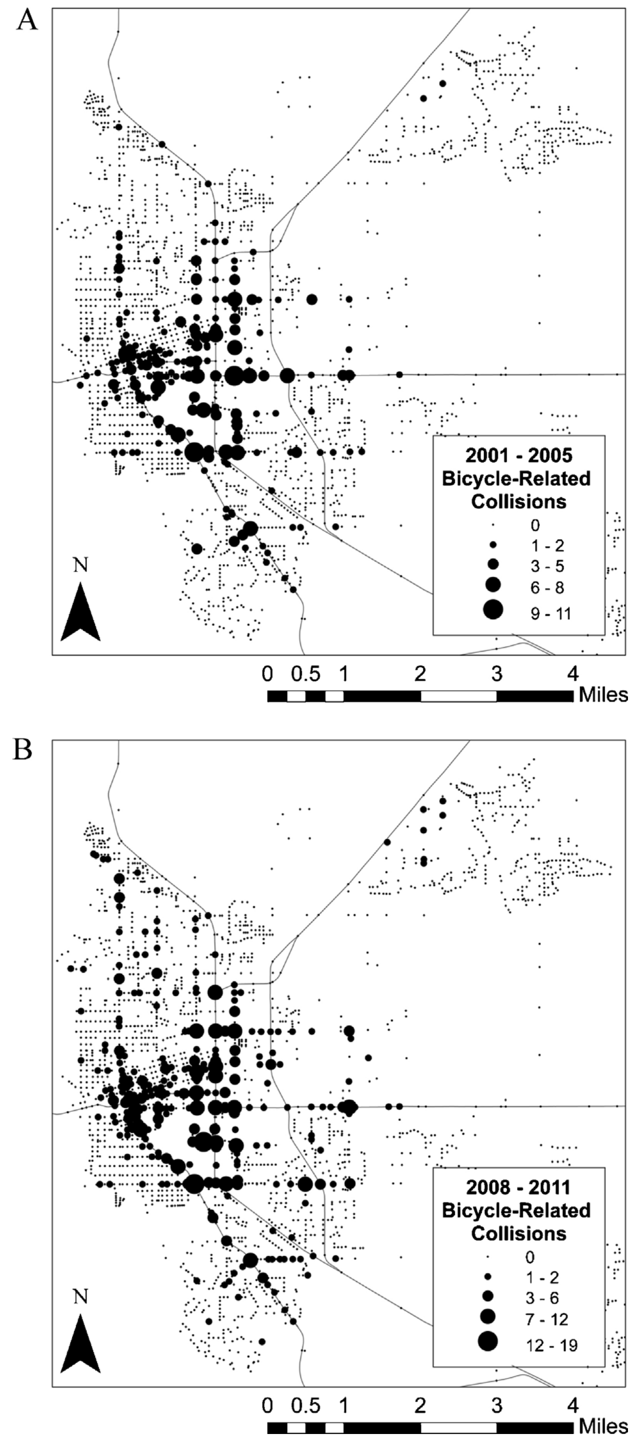

Fig. 3. Boulder motorist-cyclist intersection collisions studied.

The basic form of the negative binomial generalized linear regression model used is

$$\ln \ \mu_i = \varepsilon + \Sigma X_i \beta_n \quad (5)$$

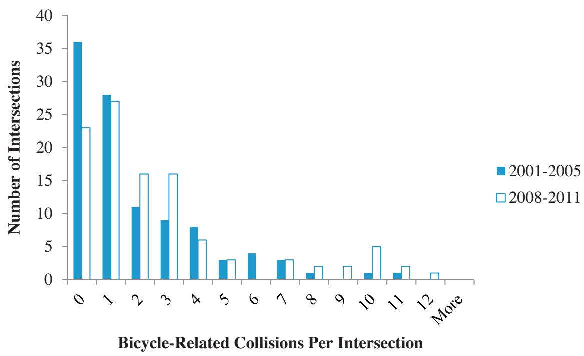

Fig. 4. Histogram of motorist-cyclist intersection collisions.

where μ_i is the randomized version of the expected number of collisions for a given traffic volume at a given intersection i; ε is the random error term, used to account for overdispersion, estimated by the model; X_i is the independent variables, in this case the natural log of the motor vehicle flow and the natural log of bicyclist flow; β_n is the estimated model parameters for motor vehicle ($n = 1$) and bicyclist volumes ($n = 2$).

Taking the exponent of both sides, the specific form of the relationship can be written

$$\mu_i = e^{\varepsilon}(AADT)^{\beta 1}(AADB)^{\beta 2} \quad (6)$$

where β_1 and β_2 are the estimated model parameters for motor vehicle and bicyclist volumes; *AADT* is the annual average daily motorized traffic passing through the intersection; *AADB* is the annual average daily bicyclist traffic passing through the intersection.

The negative binomial probability distribution is determined by Long (1997)

$$P(y_i|X_i) = \frac{\Gamma(y_i+\nu_i)}{y_i!\,\Gamma(\nu_i)}\left(\frac{\nu_i}{\nu_i+\mu_i}\right)^{\nu_i}\left(\frac{\mu_i}{\nu_i+\mu_i}\right)^{y_i} \quad (7)$$

where Γ is the gamma distribution function; ν_i is the gamma distribution parameter = 1/dispersion parameter; y_i is the number of crashes at intersection i

The variance of the negative binomial distribution is (Long, 1997)

$$Var(y_i|X_i) = \mu_i + \frac{\mu_i^2}{\nu_i} \quad (8)$$

Thus, the standard deviation of a negative binomial distribution can be computed as shown below.

$$\sigma_i = \sqrt{\mu_i + \frac{\mu_i^2}{\nu_i}} \quad (9)$$

where σ is the standard deviation for a given traffic volume at an intersection *i*.

4. Results

Parameters of the negative binomial generalized linear model were estimated by maximizing the log-likelihood using SAS 9.2 software as reported in Table 1. The low *p*-values indicate that the variables are significant. The Wald 95 percent confidence limits were computed using the Wald test, which is similar to the *t*-test. As explained by Schepers et al., "*The Wald test is a method by which the square of the ratio of a parameter estimate to its standard error is computed and tested with one degree of freedom to test the hypothesis that a certain parameter is zero*"(Schepers et al., 2011).

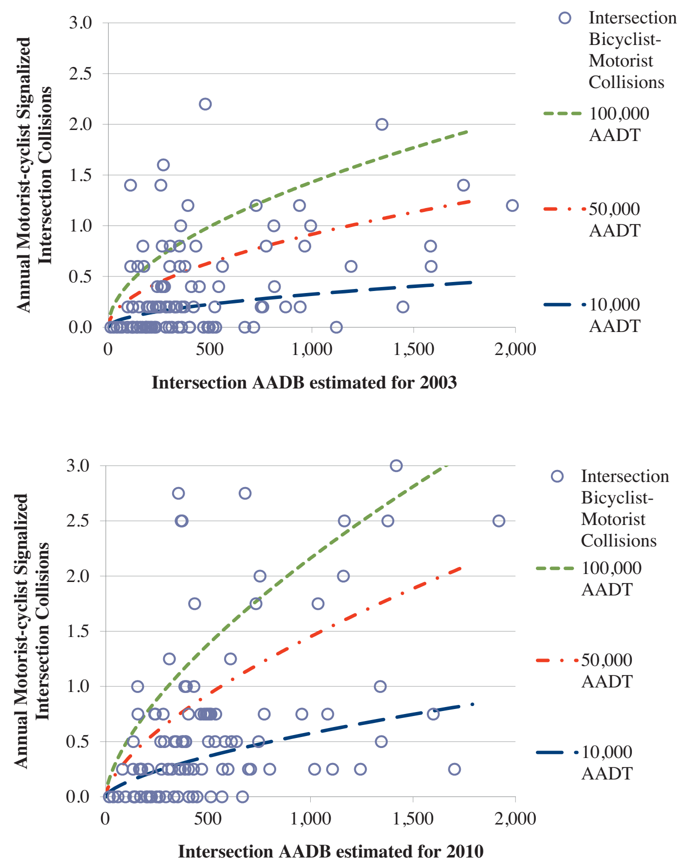

Fig. 5. Safety performance functions.

The final form of the resulting collision model is

$$C = e^{\varepsilon}(AADT)^{\beta 1}(AADB)^{\beta 2} \quad (10)$$

where *C* is the number of intersection motorist-cyclist collisions during the study period; *AADT* is the annual average daily motorized traffic passing through the intersection; *AADB* is the annual average daily bicycle traffic passing through the intersection; ε, β_1 and β_2 are the exponents estimated by the model.

To illustrate this model, two graphs have been plotted (Fig. 5). Fig. 5 depicts the safety performance function with bicyclist flow for high, medium, and low motorist volumes. These curves are similar to those plotted in the HSM.

For any SPF, the corresponding risk performance function (RPF) can be graphed by plotting collisions per vehicle on the vertical axis. The RPFs that correspond to the motorist-cyclist SPFs are presented in Figs. 6 and 7. These graphs show the chance of a collision per million cyclists passing through the intersection. A collision risk of one per million cyclists indicates that a cyclist passing through the intersection once has a one in a million chance of being involved in a collision with a motor vehicle. Like the RPFs that correspond to the SPFs in the HSM, these risk performance functions show that the chance of a collision decreases with increasing cyclist volume. In this case, the RPFs indicates that for bicyclist volumes less than 200 per day on average, risk is relatively high, while for cyclist volumes greater than 600 per day, risk is relatively low.

5. Discussion

The safety performance functions presented above may not be the final such functions for signalized intersections in the city of Boulder or for inclusion in the HSM, but they do illustrate that such functions can be created for bicyclists, and in this case, might be

Table 1
Results of negative binomial generalized linear model, maximum likelihood estimate of parameters.

2001–2005 SPF	Parameter	Estimate	Standard error	Wald Chi-square	One tailed *P*-value	Wald 95% confidence limits	
Intercept exponent	ε	−9.07	1.85	24.03	<0.0001	−12.7	−5.4
AADT exponent	β_1	0.64	0.17	15.16	<0.0001	0.31	0.97
AADB exponent	β_2	0.53	0.14	14.60	0.0001	0.26	0.79
Dispersion	$1/\nu$	0.54	0.17			0.28	1.01
2008–2011 SPF	**Parameter**	**Estimate**	**Standard error**	**Wald Chi-square**	**One tailed *P*-value**	**Wald 95% confidence limits**	
Intercept exponent	ε	−8.94	1.52	34.52	<0.0001	−11.9	−6.0
AADT exponent	β_1	0.58	0.13	32.08	<0.0001	0.31	0.84
AADB exponent	β_2	0.65	0.11	18.66	<0.0001	0.42	0.87
Dispersion	$1/\nu$	0.36	0.11			0.20	0.65

Efron's pseudo R^2 = 0.26 for model computed using Excel.
Efron's pseudo R^2 = 0.33 for model computed using Excel.

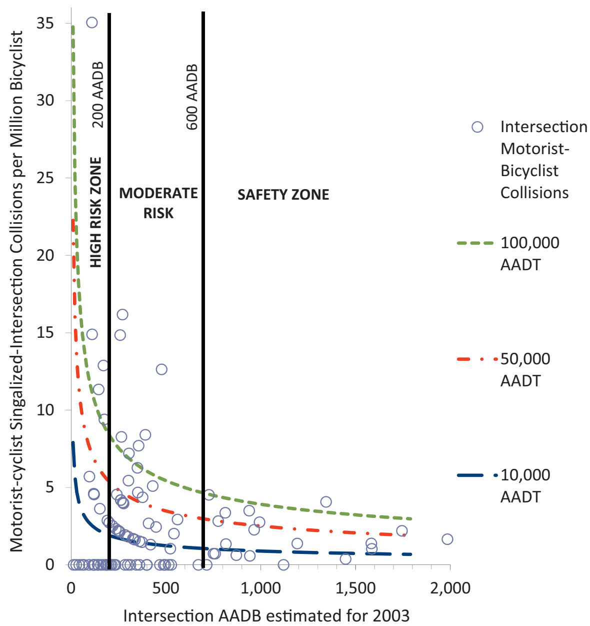

Fig. 6. Risk performance function, 2001–2005.

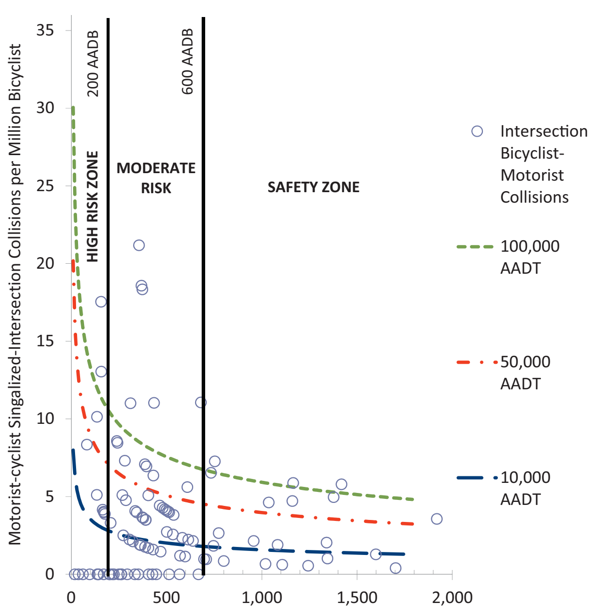

Fig. 7. Risk performance function, 2008–2011.

of use to the city of Boulder specifically. Due to AADB estimation error, these SPFs should not be considered definitive, but they do illustrate a methodology that can be replicated to develop SPFs for cyclists.

Is it possible that the error in the estimates of AADB have influenced this conclusion? To address this concern, sensitivity analyses were performed to understand how much high and low values of AADB may influence the results. When the high values of AADB were used for both datasets, the exponent for bicycle volume in the model (β_2) was still well under one, with the high end of the Wald Confidence Interval less than 0.85, indicating that the SPF is still sub-linear. When the low values of AADB were used for both datasets, the exponent for bicycle volumes approached zero, indicating that it is possible that bicycle volumes are not a large factor in determining motorist-cyclist collisions at intersections. Further analysis should investigate this possibility.

As the literature suggests, the model indicates that the more motor vehicles and the more bicyclists present on a roadway, the more bicycle-related collisions with motorists there will be. Because the exponent for bicycle volume in both models (β_2) is less than one, and the Wald 95 percent confidence interval is comfortably less than one, the models estimate that there will be fewer collisions per bicyclist with increasing bicycle volume (i.e. safety in numbers), as has been found by others (Ekman, 1996; Jacobsen, 2003). Figs. 6 and 7 illustrate this trend, showing that collisions per cyclist decrease with increasing bicycle volumes. Since similar results have been found for motor vehicles, this is not an unanticipated result, but it is indeed noteworthy, particularly for a U.S. city.

The data presented here show a connection between bicycle flow and individual bicyclist risk but do not identify the cause or direction of this connection. It may be that increased bicycling triggers safer behaviors on the part of motorists and/or bicyclists; or it may be that more bicyclists are attracted to safer facilities. Time-series collision data for intersections where infrastructure does not change, but bicycle volumes do, may help reveal the causation, but unfortunately such data are rare. It seems more likely that motorist behavior is changing with more bicycle use on a roadway, as others have hypothesized, but this is based on logical speculation rather than data analysis (Ekman, 1996).

Note that the magnitude of the exponents for both AADT and AADB is similar for both datasets. However in the first dataset, the AADT exponent exceeds that of the AADB, while for the second, the opposite is true. Other motorist-cyclist collision at intersection studies using similar model forms have found that the exponents for bicycling and motorized traffic are both less than one and range from 0.1 to 0.9, but the exponent for bicycle traffic is not necessarily less than that for motorized traffic (Elvik, 2009; Schepers et al., 2011; Turner et al., 2011).

If these exponents were the same, and AADT and AADB were of similar magnitude, it would indicate that the number of motorist-cyclist collisions is equally sensitive to both motorist and bicyclist traffic volumes. Since bicyclist traffic is one or two orders of magnitude lower than motorized traffic, the number of motorist-cyclist collisions is more sensitive to incremental increases in cyclists than incremental increases in motorists. Thus, correctly quantifying bicycle volumes is critical to correctly estimating and understanding motorist-cyclist collisions.

The SPFs developed in this study can be used to understand what a normal number of collisions at an intersection might be and from this to prioritize intersections by relative danger to cyclists. The SPFs also provide a basis from which to study the impact of spatial variables, such as type of bicycle facility, on bicyclist safety.

6. Conclusion

This analysis illustrates the potential for bicycle safety performance functions (SPFs) to be created for inclusion in future editions of the Highway Safety Manual (HSM). It also lays the groundwork for the creation of crash modification factors so that future studies can investigate the impact of specific infrastructure, speed, or other potential factors that may impact bicyclist safety. The focus of this study was not to create a definitive SPF for bicycles in the U.S., but rather to illustrate that it can be done and how to do it. Thus, this work initiates the discussion of what such a bicycle-specific SPF is, why it is important, and what it can be used for by presenting a case study for one city.

The Boulder models created in this paper illustrate the following essential points:

- Motorist-cyclist collisions at signalized intersections are significantly related to the AADT and AADB;
- Motorist-cyclist collisions at signalized intersections increase non-linearly with increasing bicyclist and motorist volumes;
- Collisions per cyclist decrease with increasing cyclist volumes; and
- The models indicate that intersections with fewer than 200 AADB have substantially higher collisions per cyclist.

Intersections with higher bicycle volumes tend to have fewer collisions per bicyclist. The safest intersections for cycling predicted by the model are those with high bicycle volumes and low motor-vehicle traffic. Thus, though no designated bicycle boulevards were included in the model, roads with low motorist traffic and high bicycle volumes, such as bicycle boulevards may minimize risk to cyclists.

Though the models presented here are specific to Boulder and it would be inappropriate to apply them elsewhere, the method for creating SPFs can and should be applied and tested elsewhere. While the findings listed above might not be observable in cities with lower bicycle volumes, cycling is increasing in cities across the U.S., making similar observations more and more possible in other cities with each passing year. Future work should include a larger dataset with more accurate estimates of AADB so that facility type can also be included in the analysis.

This effort provides the first bicycle safety performance function for a U.S. city. Much more work is needed across the country to study similar relationships. As the technology for counting bicyclists becomes more common and collisions databases improve, more bicyclist safety performance functions can be created. This may lead to potential inclusion of bicycle SPFs in future HSM editions and thus, bicycle volumes as a factor identified and used to predict bicycle collisions. This improved understanding of cyclist safety can also help lead to better understanding of what facilities are safer for cyclists, the identification of other variables that might influence cyclist safety, such as vehicle speed, land use, or proximity to transit stops, and the identification of unsafe intersections and roadways. Ultimately, this understanding can lead to higher levels of bicyclist safety, more cycling, and thus greater physical fitness and less obesity and obesity related disease.

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