What is the relation between crashes from crash databases and near crashes from naturalistic data?

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ABSTRACT

Naturalistic cycling data are increasingly available worldwide and promise ground-breaking insights into road-user behavior and crash-causation mechanisms. Because few, low-severity crashes are available, safety analyses of naturalistic data often rely on near crashes. Nevertheless, the relation between near crashes and crashes is still unknown, and the debate on whether it is legitimate to use near crashes as a proxy for crashes is still open. This paper exemplifies a methodology that combines crashes from a crash database and near crashes from naturalistic studies to explore their potential relation. Using exposure to attribute a risk level to individual crashes and near crashes depending on their temporal and spatial distribution, this methodology proposes an alternative to blackspots for crash analysis and compares crash risk with near-crash risk. The novelty of this methodology is to use exposure with high time and space resolution to estimate the risk for specific crashes and near crashes.

1. Introduction

Crashes do not randomly occur across time and space; on the contrary, they are more likely to happen at specific occasions (e.g., rush hours; Dozza, 2016) and locations (e.g., urban intersections; Wang & Nihan, 2004). These locations are often labeled as "blackspots" to warn about their potential danger (Geurts & Wets, 2003; Hauer, 1996; Nguyen, Taneeranarnon, Koren, & Luathep, 2014). However, exposure (e.g. ,number of road users or kilometers traveled) confounds blackspot locations (Higle & Witkowski, 1988), because the more road users transit a specific location, the larger the likelihood of a crash. Hence, blackspots are more likely to exist whenever and wherever traffic flow is more intense (i.e., a larger number of vehicles transits the area).

Figure 1. A hypothetical Heinrich's triangle for traffic safety, showing a possible relation between crashes and near-crashes. Please notice that the numbers are arbitrary and strongly depend on the definition of injury, damage, and near crash.

Risk, the ratio between number of crashes and exposure, is a better safety indicator than crash number alone, because exposure can vary greatly in time and space, thus influencing crash timing and locations (Elvik, 2007). For instance, by taking into account the fact that Dutch citizens cycle longer distances than French citizens, a risk analysis may show that bicycling is safer (per distance travelled) in Holland than in France, despite both countries report a similar number of bicycle crashes every year.

To enable comparisons, risk is often calculated statistically over large populations and/or long time intervals. For instance, to compare safety across European countries, road fatalities are often divided by the number of inhabitants (CARE[1], Eurostat[2]) to estimate crash risk. Travel surveys may also estimate exposure; however, because of the human observers, the collected data have a limited coverage and resolution in time and in space. Recent advances in technology make it possible to monitor traffic flow nonstop and with very high time and space resolutions. Therefore, crash risk can now be calculated on smaller time- and space-scales than ever before. In this study, we used cycling flow data to calculate risk of individual crashes, taking into account the specific time and location where each crash happened. This paper introduces a new term, *trickyspots,* which is based on individual crash risk and expands on the concept of blackspots by taking exposure with high time resolution into account when defining dangerous locations. Although previous spatial analyses created risk maps with low spatial resolution (e.g., entire stretches of a road segment; Lynam, Hummel, Barker, & Lawson, 2004) and/or used larger time scales (e.g., traffic volume over a year time; Lynam et al., 2004) our methodology can estimate risk for very specific locations (a few squared meters) and takes into account how exposure changes over the hours of a day, the days of a week, and the months of a year (Dozza, 2016).

In this paper, we use individual crash risk to explore the relation between crashes and near crashes. A large body of literature promotes near

crashes as surrogates for crashes. Furthermore, the assumption that crashes follow some sort of Heinrich's law (Heinrich, 1941) similar to the one speculated in Figure 1 is largely accepted, though yet to be proven for traffic safety. Proving the Henrich's law in traffic safety is hard for several reasons, for instance crash under-reporting makes it hard to estimate the number of crashes leading to minor or no injuries (Wegman, Zhang, & Dijkstra, 2012). Also, we still lack an objective and operational definition of what a near crash is (Dozza & González, 2013). Nevertheless, a direct relation between crashes and near crashes is often taken for granted in naturalistic data analysis when estimating crash risk (e.g., Dingus et al., 2006; Dozza, 2012; Victor, Dozza, Bärgman, Boda, et al., 2014) and this assumption affects policymaking. For instance, Hanowski, Olson, Hickman, and Bocanegra (2009) used a combination of crashes and near crashes to show that texting results in a 23-fold risk increase, triggering a ban on cellphone use for all federal employees from the president of the United States in 2009. For naturalistic cycling studies, near crashes are even more important, because these studies have so far been small and, consequently, only a few crashes have been collected (Dozza & Werneke, 2014; Petzoldt, Schleinitz, Heilmann, & Gehlert, 2016). Although some studies have argued that near crashes are indeed a solid proxy for crashes (Guo, Klauer, McGill, & Dingus, 2010), more recent studies (Dingus et al., 2016), leveraging on the largest naturalistic data set available today, have expressed serious concerns about the use of near crashes for traffic safety analyses. This paper contributes to this debate by presenting a methodology to assess the relation between crashes and near crashes. The new methodology (1) tests whether near-crash occasions and locations are indeed related to crash risk, (2) uses cycling data as an example, and (3) can be ported to data collected from any vehicle.

2. Methods

2.1 Data

The Swedish accident database, STRADA (Swedish Traffic Accident Data Acquisition), was queried for all single-bicycle crashes from 2012 to 2014 (inclusive) inside the area defined according to the World Geodetic System 1984 with latitude: 57.68–57.735 and longitude: 11.90–12.01, corresponding to downtown Göteborg. Of the 481 cases reported, 468 came from hospital reports and 20 from police reports (seven cases were found in both reports). Six cases occurred at an unknown hour of the day and were therefore excluded from the analysis. Exposure data was obtained from 11 stations which continuously measured cyclist flow and saved these data in 15-minute increments for the years 2012 to 2014 (inclusive). All stations were located in downtown Göteborg. This study also included naturalistic data, in
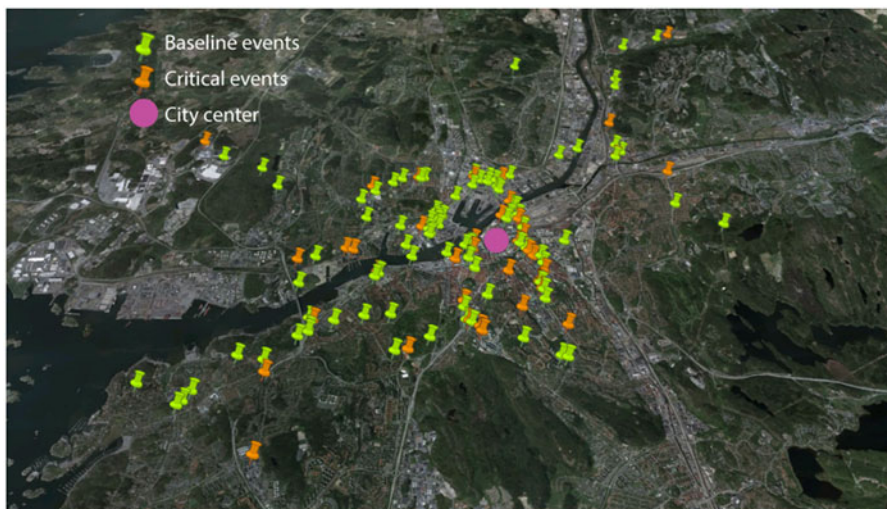
Figure 2. Critical and baseline events from BikeSAFE.

particular 30 critical and 77 baseline events from the BikeSAFE data set (Dozza & Werneke, 2014). Event selection depended on the availability of spatial and temporal coordinates. Critical events corresponded to near crashes whereas baseline events represented a random distribution of cycling events. Thus, the geographical location of the baseline events depended directly on the spatial exposure of the BikeSAFE data set. Figure 2 shows the critical and baseline events from the data set. Both types of events are concentrated in the city center because that is where the project participants cycled most.

2.2 Analysis

Crashes were clustered according to their location to identify blackspots (see analytical description in Section 2.3). Crash risk (defined as the ratio between number of crashes and number of cyclists on the road within a 1-h time window; see Section 2.3 for the analytical definition) was estimated for each crash to identify trickyspots (see Section 2.3). The crash and the cycling flow (i.e., the number of cyclists transiting a certain area at a specific time, which indicates exposure) databases were combined to create a risk map (Figure 3). On the risk map, crash risk was estimated for all crashes comparing weekdays and weekends. The cycling flow from the 11 stations was averaged. Thus, the risk map includes a spatial representation of the crash risk for all the crashes in STRADA, which depend on the temporal distribution of exposure (see Section 2.3). The risk map estimated the crash risk for each near crash and baseline event depending on their location: each near crash and baseline event received a crash risk equal to the average risk of all the crashes that happened within a specific area where the near crash or baseline event occurred. Two different area sizes were considered: 12 by 20 m (small) and 36 by 60 m (large).
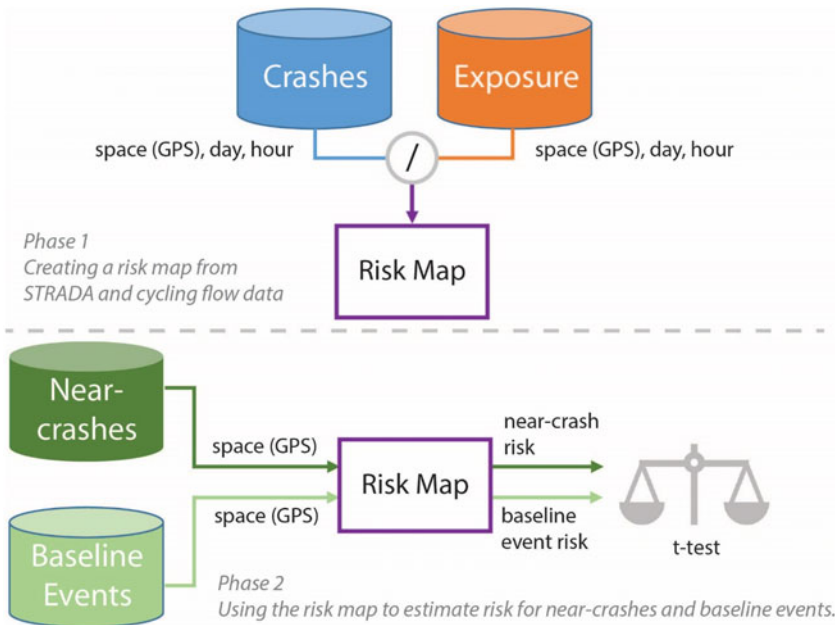
Figure 3. Analysis phases.

As summarized in Figure 3, crash risk was calculated on an hourly interval comparing weekdays and weekends as the number of crashes divided by the cyclist flow. Subsequently, near crashes and baseline events were assigned a crash risk depending on their geographical position and its proximity to crashes. Finally, the hypothesis that crash risk is higher for near crashes than baseline events was verified with a *t* test.

To demonstrate visually how crash risk is distributed geographically, this study used choropleth maps, which use color palettes to illustrate how a variable (such as number of crashes or crash risk) changes in a geographical region. In this paper, we used a full-spectrum color progression; warm colors (such as red or orange) indicate high values and cool colors (such as blue or green) low values. Thus, in a choropleth map showing crash numbers, the warmest regions indicate the blackspots (i.e., the locations where most crashes happen; see Section 2.3). Consequently, in a choropleth map showing crash risk, the warmest regions indicate the trickyspots (i.e. the locations where risk is highest; see Section).

Because only 475 crashes were available (and because crashes do not happen everywhere), the risk map did not cover all locations in downtown Göteborg; when a near crash or a baseline event happened in an area where a crash had never happened, it was not possible to compute crash risk. Odds ratios (OR; Rothman, 2012) compared the number of near crashes and baseline events for which crash risk could be computed to the
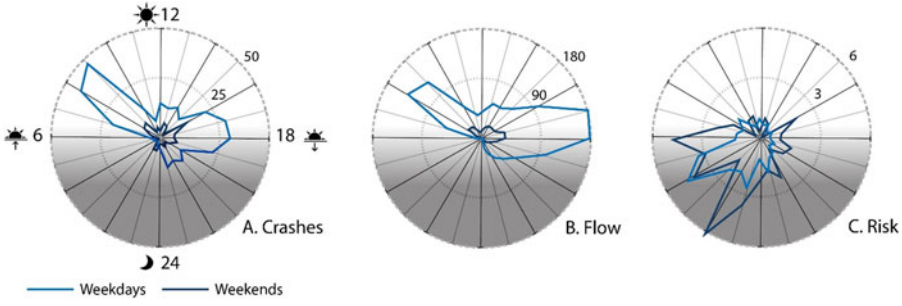
Figure 4. Crashes, flow, and risk over the 24 h for weekdays and weekends.

number for which it could not be computed. In other words, ORs considered the odds that near crashes and baseline events occurred in a location where a crash from STRADA had also happened.

2.3 Analytical description

A blackspot is a site where an unusually high number of crashes occurs. Blackspot locations are ranked by counting all crashes in different areas and then sorting the areas accordingly. A threshold value can then set the border between blackspots and nonblackspot sites. If K indicates this threshold and C_a indicates the total number of crashes in an area a, then the Boolean condition for a blackspot is:

$$\text{Blackspot}_a = \ C_a > K \tag{1}$$

The value for K may be set so that only a predetermined number of areas would satisfy the definition; Figure 5 shows blackspots with $K = 4$.

Similarly, a trickyspot is a location with an overall crash risk larger than a threshold Y. When Y is the average crash risk, trickyspots would indicate areas where risk is above average. Like K, Y may also be set so that only a predetermined number of areas satisfy the definition

The Boolean trickyspot condition for an area a is defined by the logic Equation (2):

$$\text{Trickyspot}_a = \ R_a > Y \tag{2}$$

Figure 5 shows trickyspots with $Y = 6$.

The overall risk in an area a, R_a in Equation 2, depends on how the risk for each individual crash (R_c) is computed. R_a may be defined as the average risk of all crashes taking place in a, and is independent of R_c. In Equation 3, C_a indicates the number of crashes which took place in a.

$$R_a = \frac{\sum_{c=0}^{C_a} R_c}{C_a} \tag{3}$$
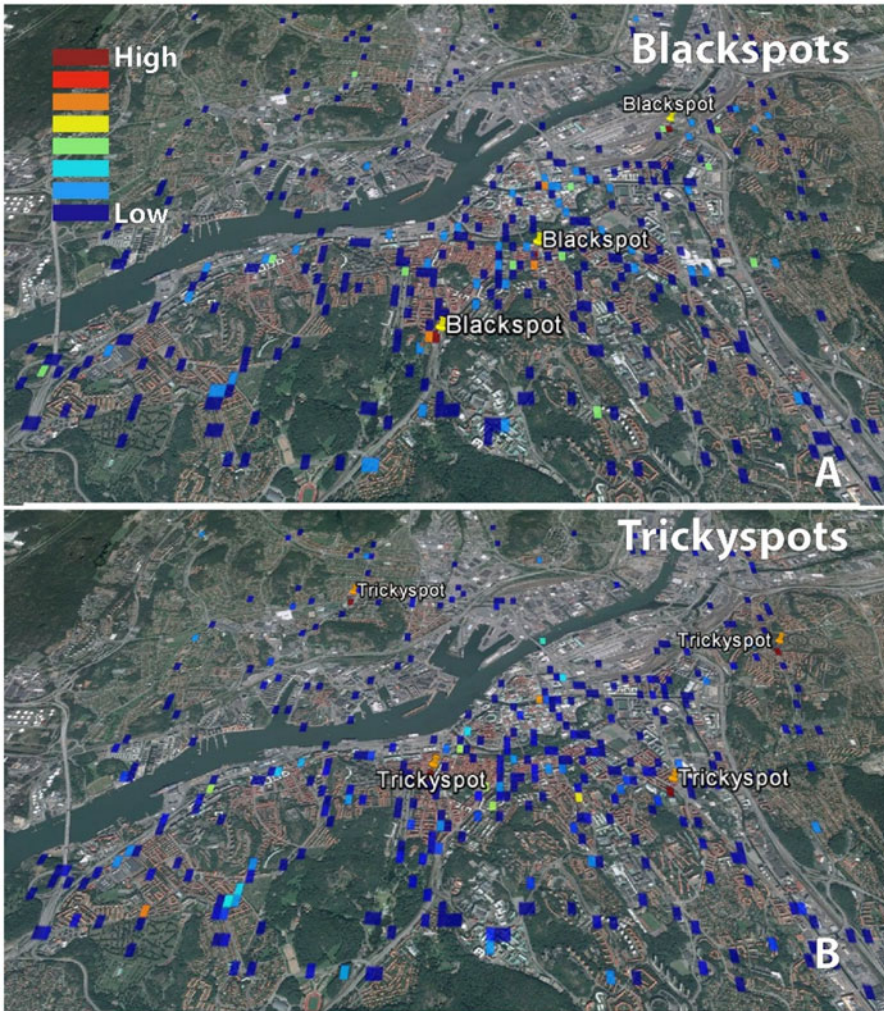
Figure 5. Geographical maps of Göteborg with heat maps coding for crash number (A) and crash risk (B).

In general, individual crash risk, R_c in Equation 2, depends on the flow in the area a at the time of each individual crash c.

Equation 4 offer a simplified definition of crash risk that takes time (specifically, hour of the day and whether it is a weekday/weekend), but not geography, into account. This paper used this definition to demonstrate how the proposed methodology may help assess the relation between near crashes and crashes. According to this definition, the overall risk of a crash in an area a may be generally described as:

$$R_c = R(h_c, d_c) \tag{4}$$

Where, $R(h_c, d_c)$, the risk for the hour and the day when the crash c occurred (h_c and d_c, respectively), can be defined as the ratio between (1)

the proportion of crashes happening on the same day and hour as the crash and (2) the proportion of cyclists in traffic on the same day and hour (Equation 5).

$$R(h_c, d_c) = \frac{\frac{N(h_c,d_c)}{N(h_c)}}{\frac{E(h_c,d_c)}{E(h_c)}} \tag{5}$$

The numerator in Equation 5 is the percentage of crashes happening on the same day and hour when the crash c occurred compared to all crashes happening on the same day and hour as crash c, but on the other days. The denominator is the percentage of cyclists in traffic at the same hour and day when the crash c occurred compared to cyclists in traffic at the same hour as crash c, but on different days.

$$R_a = \frac{\sum_{c=0}^{C_a} \frac{\frac{N(h_c,d_c)}{N(h_c)}}{\frac{E(h_c,d_c)}{E(h_c)}}}{C_a} \tag{6}$$

Equation 6, derived by combining Equations 3–5, is only defined when exposure is different from zero for any day of the week and hour of the day, when at least one crash occurred in the area a. It is worth noting that this is not necessarily a limitation. It is merely a logic consequence of the definition of risk; in fact, when no traffic is present no crash should (can) happen. Interestingly, omitting the denominator in Equation 6 corresponds to calculating the cumulative risk instead of the relative risk in an area a. This cumulative risk, the simplest method for combining trickyspots and blackspots, is addressed in the Discussion.

3. Results

3.1 Phase 1: Creating a risk map from STRADA and cycling flow data

In general, when more cyclists were in traffic, more single-bicycle crashes occurred (Figures 4A–B). Crashes happened more often on weekdays than on weekends. Cyclist flow and crash numbers followed a different pattern over time for weekends compared to weekdays; in fact, during weekdays, rush hours modulated cyclist flow and crash numbers, whereas during weekends cyclist flow and crash numbers were highest in the afternoon (as previously found in Dozza, 2016). Figure 4 shows crash data, cycling flow data, and crash risk distributed across hours of the day, comparing weekdays to weekends. Risk was higher after midnight than during the day, and on weekends than on weekdays (Figure 4C). Risk at commuting time (when cycling flow and crashes were most prevalent) was lower than average (Figure 4C).

Table 1. Comparison between near-crashes and baseline events: Odds ratio (OR) and crash risk.

	Small areas			Large areas			
	Where a crash also happened	Where no crash happened	OR (confidence intervals [CI])	Where a crash also happened	Where no crash happened	OR (CI)	Risk $M \pm SD$
Near crashes	4	26	1.3 [0.1, 3.6]	12	18	1.1 [0.5, 2.6]	1.30 ± 0.49
Baseline events	8	69		29	47		1.18 ± 0.48

Blackspots and trickyspots appeared in different locations. The top three blackspots had nine, eight, and five crashes (Figure 5A). The top four trickyspots had crashes on weekend nights when risk was highest; Figure 5B).

3.2 Phase 2: Using the risk map to estimate risk for near crash and baseline events

More often than baseline events, near crashes took place in areas where crashes also happened (Table 1). As the size of these areas increased from small to large, the number of near crashes and baseline events which took place in them also increased (Table 1), while their proportion evened up. OR analysis revealed that the probability of an event taking place in an area where a crash also happened was higher for near crashes than for baseline events, being 1.3 times higher for small areas and 1.1 times higher for large areas (Table 1). For small areas, it was not possible to statistically compare crash risk between near crashes and baseline events because the data sample was too small. However, when crash risk was computed from large areas, near crashes showed a higher crash risk than baseline events; nevertheless, this difference was not statistically significant from a t test (Table 1).

4. Discussion

This paper combines crash databases, naturalistic data, and cycling flow data to demonstrate a methodology assessing the relation between crashes and near crashes to help determine the ecological validity of analyses using crash surrogates. Crash surrogates are not only used in naturalistic studies to assess safety for all kinds of road users (Dozza, Bianchi Piccinini, & Werneke, 2016; Olson, Hanowski, Hickman, & Bocanegra, 2009; Petzoldt et al., 2016; Victor, Dozza, Bärgman, Engström, et al., 2014) but are also the basis for conflict techniques such as the Swedish traffic conflict technique (Hydén, 1996), the Dutch conflict technique DOCTOR (van der Horst & Kraay, 1986), and the probabilistic surrogate measures of safety technique from Canada (Saunier, Sayed, & Ismail, 2010). Using crash

surrogates is particularly important for cycling safety analyses because bicycle crashes are largely under-reported and crash databases include very little information on bicycle crashes. The methodology presented in this paper can determine whether near crashes are a sound proxy for crashes, to what extent specific types of near crashes predict specific types of crashes, and which factors may change the relation between crashes and near crashes.

It is worth noticing that, though naturalistic datasets are continuously growing in size, the number of crashes in naturalistic datasets is still very limited; the largest naturalistic driving data set, collected by the second Strategic Highway Research Program (SHRP2) (Campbell, 2013), contains about 900 crashes, including all crash scenarios, environmental conditions, and road users. As soon as an analyst filters these crashes by incident type, weather conditions, or demographics, it may be necessary to include near crashes to achieve statistical significance of the results. Additionally, though it is true that naturalistic data sets continue to grow, near crashes will always be more numerous than crashes and have the intrinsic potential to improve the timely prediction of safety issues. In other words, if near crashes are indeed related to crashes, waiting to collect enough crash data to perform safety analyses may be inefficient and unethical.

The results presented in this paper hint to a possible relation between crashes and near crashes, because near crashes were more likely to happen in a location where a crash also happened than baseline events were, and the crash risk was larger for near crashes than for baseline events. Furthermore, the fact that OR decreased as the areas expanded is in line with our assumption that the higher spatial and temporal resolution in the risk map, the closer the relation between crashes and near crashes. Nevertheless, none of the results in this paper reached statistical significance and, because the data was very limited, some simplifications were necessary to perform the analysis. The main simplifications came from (1) averaging cyclists' flow across measuring stations, and (2) averaging crash and exposure data across years. Minor simplifications included using a low geographical resolution (relatively large areas) to estimate risk. It is indeed surprising that, with such a small data set and these simplifications, the results could still show the expected trends. The following list of recommendations shows how the analysis in this paper might be improved to show sound evidence about the relation between crashes and near crashes. The methodology might also be able to answer new questions, such as, "To what extent do specific types of near crashes predict specific types of crashes?" and "Which factors may change the relation between crashes and near crashes?" thus contributing to an objective definition of what a near-crash is (Dozza & González, 2013). The items in this list are often

independent from each other and may be equally important for obtaining significant results.

1. More crashes and near crashes should be included. As naturalistic data sets grow, it may be possible to use a larger geographical area and longer intervals of data collection. Crashes from insurance companies (e.g., Isaksson-Hellman, 2012), may also be included to increase the data set and control at least in part for underreporting in crash databases (Wegman et al., 2012).

2. Cycling flow should be calculated on an individual street level. New models, such as the one proposed by Loidl, Traun, and Wallentin (2016) who explored different spatial scales for the analysis of urban bicycle crashes, may help increase cycling flow resolution without necessarily monitoring all streets.

3. The spatial resolution of the risk map should be higher. As the data sample increases, aggregation areas smaller than the small one presented in this paper (12 m by 20 m) should be considered. The current GPS resolution (about 6 m in naturalistic data sets) sets a clear lower limit on the size of these areas, which will hopefully be overcome when better positioning technology is available.

4. The time resolution of the risk map should be higher. This study used a 1-h resolution; however, when more crashes and near crashes become available, using the native resolution of cycling flow data (15 min) seems more appropriate because cycling flow may change during one hour. Furthermore, the higher the time resolution the more likely it is for cyclists to be double counted, because they may pass several measuring stations within the time interval.

5. The individual year and day of the week of the crashes and near crashes should also be considered. In this study, data was averaged across years and divided into weekdays and weekends. As more data becomes available, it may be possible to average crashes and near crashes differently across time. However, as crashes and near crashes are not continuously happening in all locations, some level of time aggregation will always be necessary.

6. Factors other than exposure should be included in the risk map to help identify the relation between crashes and near crashes while also serving to identify the main contributing factors for crash causation. Several factors, such as weather and infrastructure, are already coded in crash databases and naturalistic data sets and could be used to determine how these factors mediate the relation between crashes and near crashes.

7. The potential effect of underreporting should be taken into account. Less severe crashes are also less likely to be reported, so it may be hard

to determine the values for the middle layers of the Heinrich's triangle in Figure 1, and near crashes that can only predict minor severity crashes may be underestimated.

8. Motorized vehicle flow should also be considered and other crash types than single-bicycle crashes should be included. In this paper, we only selected single-bicycle crashes because our measure of exposure was cycling flow; crashes between a bicycle and a motorized vehicle may depend also on motorized-vehicle flow and were therefore excluded. Nevertheless, the extent to which motorized vehicles may have contributed to the single-bicycle crashes (and/or the near crashes) used in this study is unknown.

As future analyses increase temporal and spatial resolution of the risk map, they may also suffer to a larger extent from regression to the mean (Hauer, 1986) and accident migration (Elvik, 1997) than the present analyses. Nevertheless, current models to adjust for such effects may be ported to this methodology to weight risks.

This study defined trickyspots based on the spatial distribution of crash risk. This metric is particularly sensitive to those locations where crashes happen despite few cyclists transiting them. In contrast, blackspots identify where most crashes happen and may still be a reasonable indicator for geographically prioritizing countermeasures. However, trickyspot analysis may help identify locations where simple interventions (such as improving deceptive infrastructure or signage) could have a large safety impact. In fact, while blackspots may occur simply because of a large traffic flow, trickyspots require some unusual rate of crashes and road users. Although it was not the case in this study, it is possible for a blackspot to also be a trickyspot, in which case the potential safety benefit from crash reduction in that location would be particularly high. Thus, combining trickyspot analysis with blackspot analysis may help the ranking and selection phase of the analysis. (Section 2.3 provides a simple equation combining the analysis of blackspots and trickyspots.) Let us keep in mind that what really matters for safety are the causes of a crash; trickyspot analysis may highlight locations where these causes are particularly odd, possibly making the causes easier to identify.

4. Conclusions

The relation between crashes from crash databases and near crashes from naturalistic data can be assessed by comparing the spatial-temporal distributions of crashes and near crashes. This paper proposes a methodology for the comparison and applies the methodology to cycling data in

Göteborg. The methodology leverages on cycling flow to estimate individual crash risk and create a risk map that represents crash risk with a high temporal and spatial resolution. The novelty of this methodology is to use exposure with high time and space resolution for the estimation of risk for specific bicycle crashes and near crashes.

Although the results presented in this paper may suggest that there is indeed a relation between crashes and near crashes, the main contribution of this paper is the methodology itself. In fact, the results in this study suffer from the small data sets available, which required some oversimplification of the analysis. When larger data sets become available, this methodology may provide results that are significant and answer further questions on the relation between crashes and near crashes.

This study also proposes the concept of trickyspots as a complement to blackspots for the selection and ranking of dangerous locations. Although defining *trickyspots* may not be straightforward for all crash types because exposure may be difficult to define and obtain, doing so may highlight locations where crashes happen for unusual reasons, reasons that may be easier to identify and control because of their oddity.

Notes

1. http://ec.europa.eu/transport/road_safety/specialist/statistics/index_en.htm
2. http://ec.europa.eu/eurostat/statistics-explained/index.php/Transport_accident_statistics#Road_accident_statistics

Acknowledgments

References

Campbell, K. L. (2013). The SHRP 2 Naturalistic Driving Study: Addressing driver performance and behavior in traffic safety. TR News, 282.

Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. Proceedings of the National Academy of Sciences, 201513271.

Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J., … Knipling, R. R. (2006). The 100-Car Naturalistic Driving Study - phase II - results of the 100-car field experiment. Technical Report, DOT HS 810.

Dozza, M. (2012). What factors influence drivers' response time for evasive maneuvers in real traffic? *Accident Analysis and Prevention*, 58, 299–308. https://doi.org/10.1016/j.aap.2012.06.003

Dozza, M. (2016). Crash risk: How cycling flow can help explain crash data. *Accident Analysis & Prevention*, *105*, 21–29.

Dozza, M., Bianchi Piccinini, G., & Werneke, J. (2016). Using naturalistic data to assess e-cyclist behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, *41*, 217–226. http://dx.doi.org/10.1016/j.trf.2015.04.003

Dozza, M., & González, N. P. (2013). Recognising safety critical events: Can automatic video processing improve naturalistic data analyses? *Accident Analysis and Prevention*, *60*, 298–304. doi:10.1016/j.aap.2013.02.014

Dozza, M., & Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world? *Transportation Research Part F: Traffic Psychology and Behaviour*, *24*, 83–91. doi:10.1016/j.trf.2014.04.001

Elvik, R. (1997). Evaluations of road accident blackspot treatment: A case of the Iron Law of evaluation studies? *Accident Analysis and Prevention*, *29*(2), 191–199. doi: https://doi.org/Doi10.1016/S0001-4575(96)00070-X

Elvik, R. (2007). *State-of-the-art approaches to road accident black spot management and safety analysis of road networks*. Oslo: Transportøkonomisk institutt.

Geurts, K., & Wets, G. (2003). *Black spot analysis methods: Literature review*. The Hague: Kennis Verkeersonveiligheid

Guo, F., Klauer, S. G., McGill, M. T., & Dingus, T. A. (2010). Evaluating the relationship between near-crashes and crashes: Can near-crashes serve as a surrogate safety metric for crashes? Technical Report (Vol. DOT HS 811).

Hanowski, R. J., Olson, R. L., Hickman, J. S., & Bocanegra, J. (2009). Driver distraction in commercial vehicle operation. *Driver Distraction and Inattention Conference*.

Hauer, E. (1986). On the estimation of the expected number of accidents. *Accident; Analysis and Prevention*, *18*(1), 1–12.

Hauer, E. (1996). Identification of sites with promise. *Transportation Research Record: Journal of the Transportation Research Board*, *1542*(1), 54–60. doi:10.1177/0361198196154200109

Heinrich, H. W. (1941). *Industrial accident prevention. A scientific approach* (2nd edn.). New York: McGraw-Hill.

Higle, J. L., & Witkowski, J. M. (1988). Bayesian identification of hazardous locations (with *d*iscussion and *c*losure). Washington, DC: Transportation Research Board

Hydén, C. (1996). *Traffic conflicts technique: state-of-the-art*. In H. H. Topp (Ed.) Traffic safety work with video-processing. Washington, DC: Transportation Department, University Kaiserlauten.

Isaksson-Hellman, I. (2012). A study of bicycle and passenger car collisions based on insurance claims data. *Annals of Advances in Automotive Medicine. Association for the Advancement of Automotive Medicine. Annual Scientific Conference*, *56*, 3–12. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/23169111

Loidl, M., Traun, C., & Wallentin, G. (2016). Spatial patterns and temporal dynamics of urban bicycle crashes-A case study from Salzburg (Austria). *Journal of Transport Geography*, *52*, 38–50. doi:10.1016/j.jtrangeo.2016.02.008

Lynam, D., Hummel, T., Barker, J., & Lawson, S. D. (2004). European Road Assessment Programme EuroRAP I (2003) Technical Report. EuroRAP May.

Nguyen, H. H., Taneerananon, P., Koren, C., & Luathep, P. (2014). The evolution of criteria for identifying black spots and recommendations for developing countries. *Journal of Society for Transportation and Traffic Studies*, *5*(3), 199–209

Olson, R. L., Hanowski, R. J., Hickman, J. S., & Bocanegra, J. (2009). Driver distraction in commercial vehicle operations. *Technical Report, FMCSA-RRR-*(Final Report).

Petzoldt, T., Schleinitz, K., Heilmann, S., & Gehlert, T. (2016). Traffic conflicts and their contextual factors when riding conventional vs. electric bicycles. *Transportation Research Part F: Traffic Psychology and Behaviour*, 46, 477–490.

Rothman, K. J. (2012). *Epidemiology: An introduction*. Oxford: Oxford University Press.

Saunier, N., Sayed, T., & Ismail, K. (2010). Large-scale automated analysis of vehicle interactions and collisions. *Transportation Research Record: Journal of the Transportation Research Board*, 2147(1), 42–50. doi:10.3141/2147-06

van der Horst, R., & Kraay, R. J. (1986). The Dutch Conflict Technique—DOCTOR. In ICTCT Workshop, Budapest.

Victor, T., Dozza, M., Bärgman, J., Boda, C. N., Engström, J., Flannagan, C., & Markkula, G. (2014). Analysis of Naturalistic Driving Study data: Safer glances, driver inattention, and crash risk SHRP 2 safety project SO8A. Washington, DC: *Transportation Research Board of the National Academies*. SHRP.

Victor, T., Dozza, M., Bärgman, J., Engström, J., Flannagan, C., & Boda, C. (2014). *Safer Glances - SAFER SHRP 2 S08 Final report*.

Wang, Y., & Nihan, N. L. (2004). Estimating the risk of collisions between bicycles and motor vehicles at signalized intersections. *Accident Analysis & Prevention*, 36(3), 313–321. doi:10.1016/S0001-4575(03)00009-5

Wegman, F., Zhang, F., & Dijkstra, A. (2012). How to make more cycling good for road safety? *Accident Analysis and Prevention*, 44(1), 19–29. doi:10.1016/j.aap.2010.11.010