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Mapping bicycling exposure and safety risk using Strava Metro

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ABSTRACT

Overcoming concerns about bicycling safety is critical to increasing the health benefits of bicycling for transportation. While exposure measures are critical for monitoring and understanding bike safety, lack of spatially and temporally detailed bike counts makes it challenging to conduct robust bicycling safety studies. Crowdsourced data from smartphone apps like Strava provide counts for nearly all individual road and trail sections with 1-min temporal resolution. Researchers have found that patterns of Strava bicyclists are similar to all bicyclists in our study area. In this paper, we develop and test a method to normalize bike safety incident hotspots using exposure estimated from Strava data for Ottawa, Canada. We mapped incident hotspots normalized by exposure at increasingly detailed temporal scales. In a dataset with more than more than 8 million Strava activities and 395 incidents (approximately 20,000 Strava activities per incident), adjusting for exposure moved incident hotspots away from protected bike lanes and multi-use paths and onto commercial streets with no bike infrastructure. Strava data are available to correct for exposure where other measures are not available. We encourage researchers, planners, and public health practitioners to consider crowdsourced data to fill exposure data gaps and provide context for interpreting incident data.

1. Introduction

To increase access to the health benefits of bicycling it is important to overcome safety concerns of bicyclists and potential bicyclists. As such, robust bicycling safety research is needed but is often limited by lack of exposure data. Without exposure data safety studies cannot determine the cause of high numbers of crashes or near misses, which could relate, for example, to an infrastructure issue or simply be attributable to a large number of bicyclists. As with motor vehicle safety, exposure data allow for the calculation of risk to determine the incident rates per trip or per kilometer traveled, enhancing the contextual interpretation (Kweon & Kockelman, 2003; Vanparijs, Int Panis, Meeusen, & De Geus, 2015). Lack of consideration of exposure can result in misleading conclusions when comparing locations across a city and is also problematic for safety monitoring. For example, if new bicycle infrastructure results in an increase in the number of bicyclists, the total number of bicycling incidents could increase even while the actual rate of bicycling incidents declines.

Many studies on bicycling safety do not include exposure, as such data are often unavailable (Beck, Dellinger, & O'Neil, 2007). Studies that do include exposure have used estimates based on time (Rodgers, 1995) or trips traveled at a population level (Beck et al., 2007). These studies examine the safety of bicycling relative to other travel modes (Beck et al., 2007) and the demographics of the bicyclist (Rodgers, 1995), but not the specific routing or type of infrastructure involved.

Exposure is important for understanding bicycling safety. With more motorized and non-motorized travel, the number of incidents will increase following a nonlinear relationship (Osama & Sayed, 2017). For example, researchers have found safety in numbers for bicycling: where there are more bicycling trips there are lower bicycle crash rates since riders choose safe routes and motor vehicle drivers are forced to pay attention to non-motorized travelers (Prato, Kaplan, Rasmussen, & Hels, 2016). Likewise, with more motorized traffic, bicycle crash rates involving motor vehicles also decrease, since motor vehicle travel speeds are lower in congested traffic (Prato et al., 2016). However, these studies used aggregate traffic analysis zones to support broad-scale planning and understanding the determinants of bicycling safety, and new approaches are needed to incorporate exposure into studies that use site-specific spatial analysis approaches for bicycling safety, such as kernel density estimates (KDE) (Harirforoush & Bellalite, 2019). KDE

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approaches are appealing for use in practice since they are accessible within GIS software, the maps and visualizations are intuitive, and these approaches can be applied at spatially detailed scales that are appropriate for finding priority locations for infrastructure improvements within a city (Bíl, Andrášik, & Sedoník, 2019). Quantifying the density of bicycling trips across the transportation network (bicycling exposure) provides essential context by distinguishing locations that have high numbers of bicycling trips and few incidents (indicating low risk) from locations that have few bicycling trips and few incidents (which may be high risk but have no incident reporting) (Boss, Nelson, & Winters, 2018).

Using traditional approaches, it is difficult to obtain ridership data that are spatially and temporally detailed. The Canadian census provides data on the primary mode for journey to work, but does not consider other trips and has no information on the route. Ridership data can also be collected either using permanent or temporary counters. While permanent counters usually capture fine temporal detail, they lack spatial variation needed to map ridership across the city. In contrast, temporary count stations and volunteer count programs can have greater spatial detail but are limited in temporal scope and may not capture seasonal pattern changes. For example, cities with snowy winters may see bicyclists choose different routes during winter months. Similarly, ridership near a university campus might plummet in summer months (Griffin, Nordback, Götschi, Stolz, & Kothuri, 2014).

Physical activity apps, such as Strava, are used to track individual activity. Strava has millions of users globally who are creating a comprehensive database of ridership (Conrow, Wentz, Nelson, & Pettit, 2018). Strava data are very high resolution, with data available for nearly every street and intersection with 1-min temporal resolution. Strava data only captures a subset of bicyclists - those who use the app (Conrow et al., 2018). Research led by our team is developing tools to correct the bias in Strava data to represent all ridership (Roy et al., 2019). Using GIS data and statistical modeling researchers have demonstrated that it is possible to correct the sampling bias in Strava data to within 50 average annual daily bicyclists for up to 80% of street segments (Roy et al., 2019). However, it has also been shown that the patterns of ridership represented by Strava bicyclists is a good indicator of the pattern of all bicyclists in urban areas (Jestico, Nelson, & Winters, 2016). In other words, when the network is limited, as it is in a city center, Strava bicyclists take similar routes to all bicyclists. While the absolute number of bicyclists will not be well represented by Strava data, the relative use of a road is well represented in the city.

Our goal is to develop and test a method of identifying and normalizing bike safety incident hotspots using exposure estimated from Strava data. We demonstrate the use of Strava for exposure by mapping bike incident hotspots in Ottawa. We map raw incident hotspots, exposure from Strava, and normalized incident hotspots using a range of timeframes with increasing temporal detail (all Strava activities 2015–2016, seasonal ridership, and ridership by peak travel and weekday/weekend) and demonstrate how definitions of exposure give nuance to where bike incident hotspots are mapped.

2. Material and methods

Ottawa, Ontario is a Canadian city with a population of 1.3 million, bicycling mode share of 2% (Statistics Canada, 2019), and a growing network of bicycling infrastructure. The city owns more than two years of Strava Metro. We selected a study area within the city center, covering 19 km^2, including a range of bicycle infrastructure and encompassing all of the city's 12 automated bike counters. To minimize edge effects, the study area was delineated using natural and manmade boundaries including the Ottawa River, Rideau River, Dow's Lake, and the Trillium Line (O-train) tracks.

Incidents were acquired from official and crowdsourced sources for 2015 and 2016. Official bike incidents recorded by the Ottawa Police were provided by Bike Ottawa (https://bikeottawa.ca/collisions/), numbering 312 in the study area. Crowdsourced collisions and near misses were acquired from BikeMaps.org (Nelson, Denouden, Jestico, Laberee, & Winters, 2015), numbering 83 in 2015 and 2016.

Table 1
Can-BICS labels for data acquired from the City of Ottawa open data.

Can-BICS classification	Can-BICS name	Ottawa open data name
I. High comfort	Cycle track	Cycle track or segregated bike lane*
II. Medium comfort	Multi-use path	Path
III. Low comfort	Painted bike lane	Bike Lane, or shoulder

* Can-BICs includes local-street bikeways (i.e. local–streets with traffic calming or traffic diversion measures) in Class I, but we didn't find this type of infrastructure in Ottawa's open data (based on reviewing Google Street View imagery and street network data). For our analysis, we included a fourth separate category for the streets labeled in open data as "suggested routes", since these are relevant for planning future bike infrastructure and may influence individuals' route choices.

Exposure data were acquired from Strava Metro (https://metro.strava.com/). We analyzed the core street-level data (1-min resolution) by summing the total activity count (i.e., the count of bike trips on each road or trail section) for each edge (i.e., the section of road or trail between intersections) for the selected timeframes (described below) to find the total Strava activities.

To understand bicycling safety at a range of temporal scales, we analyzed the incidents and exposure within timeframes with increasing temporal resolution. At the coarsest scale, we analyzed all incidents and Strava activities for 2015 and 2016. At the seasonal scale, we compared months with winter riding conditions (November to March, months with a minimum average daily temperature below zero degrees Celsius) with the months with summer riding conditions (April to September)(Government of Canada, 2019). At the daily scale, we compared business days with weekends and holidays. At the sub-daily scale, we compared peak commute times (7–9 am and 3–6 pm) on business days with all other times on business days.

To convert the point- and line-based events (incidents and Strava activities, respectively) to units that represent areas with higher densities of events, we calculated kernel density estimates (KDE). For the incidents, we used a Gaussian kernel with 10 m spatial resolution and tested bandwidths from 50 m through 400 m in 50 m increments. We chose to use a 100 m bandwidth, since this provided identifiable incident hotspots at approximately the scale of one city block, which is appropriate for evaluating bike infrastructure in an urban context. We used the same resolution for the KDE of Strava activities. KDEs were calculated using the R Package spatstat version 1.59–0 and the functions density.ppp (for incidents) and density.psp (for Strava activities) (Baddeley & Turner, 2005).

To normalize the KDE for incidents using the KDE for Strava activities we divided the raster layers (incidents/exposure). We calculated the percentile rank and defined incident hotspots as the top 10 percent of values. Raster division and processing were completed using the R package raster (Hijmans, 2019).

To quantify how the incident hotspots related to the underlying street infrastructure and support the interpretation of hotspot maps, street network data were downloaded from OpenStreetMap (OpenStreetMap Contributors, 2019) using the query "highway = *" using Overpass Turbo (https://overpass-turbo.eu/). We excluded features with "highway = path", since these represented sidewalks. We then calculated the percent length for streets with speed limits above 50 km/h relative to the total length of streets within the incident hotspots. Bike infrastructure data were downloaded from the City of Ottawa Open Data, using a version last updated in 2016 (http://data.ottawa.ca/dataset/cycling-network). We used the Can-BICS (Canadian Bikeway Comfort and Safety) classification system (Winters, Zanotto, & Butler, 2020) to identify classes of bicycle infrastructure based on safety and comfort (Table 1). Within the incident hotspots, we then calculated the percent

Table 2
Data summary for incidents and exposure for the entire study area.

Timeframe	Incidents	Exposure (Strava activities)	Incidents: Activities
1. All	395	8,030,359	1:20,330
2. Season			
a) Summer	350	7,445,592	1: 21,273
b) Winter	45	584,767	1: 12,995
3. Business day vs weekend/holiday			
a) business day	339	1,787,125	1: 5272
b) weekend or holiday	56	6,243,234	1: 111,486
4. Peak commute times			
a) 7–9 am business days	93	374,434	1:4026
b) 3–6 pm business days	122	410,038	1:3360
c) All other times business days	124	1,002,653	1:8086

length for each Can-BICS class relative to the total length.

3. Results

There were more than 8 million Strava activities in the study area and 395 incidents, corresponding with approximately 1 incident for every 20,000 Strava activities (Table 2). The incident rate was higher for winter riding conditions than during summer riding conditions. Most of the Strava activities occurred on weekends and holidays, and this time had the lowest incident rate. The afternoon commute period had the highest incident rate.

The largest raw incident hotspots were located in the downtown core along Laurier Avenue, where there is a protected bike lane (Fig. 1a). The exposure KDE for Strava activities showed a high density of activities along multi-use paths along the Rideau Canal, along the Ottawa River, on the Trillium multi-use trail, and on protected bike lanes on Laurier Avenue in the downtown core (Fig. 1b). When the incident hotspots were normalized for exposure (e.g., incidents/Strava) the resulting normalized hotspots were smaller in the downtown core (i.e. along Laurier Avenue), and the largest normalized incident hotspots were on Bronson Avenue, a site with four lanes for motor vehicles and no bike infrastructure and it is not a suggested bike route (Fig. 1c). There were also no normalized incident hotspots along multi-use paths. The map for winter (not shown) revealed that incidents were spatially dispersed, and we were not able to generate meaningful incident hotspots.

Comparing business days with weekends and holidays, there were notable differences in the location of normalized incident hotspots with more normalized incident hotspots located in the city center and bridges on business days and outside the downtown core (i.e. away from Laurier Avenue) on weekends and holidays (Fig. 2A). On weekends and holidays, normalized incident hotspots were concentrated on commercial streets outside of the downtown core (Fig. 2B).

Both morning and afternoon peak commute times had normalized incident hotspots on separated bike lanes on Laurier Avenue (Fig. 3a and b). Other times on business days showed normalized incident hotspots on Bronson Avenue and Bank Street, both commercial streets without bicycling facilities (Fig. 3c).

The locations of incident hotspot were related to the underlying transportation infrastructure (Table 3). Compared to the proportions for all infrastructure in the study area, all of the incident hotspots (defined by the top 10% of the KDE) had a greater proportion of streets with speed limits above 50 km/h, low comfort bike infrastructure, and suggested bike routes. In contrast, compared to the greater study area, the incident hotspots had a lower proportion of high and medium comfort bike infrastructure. Much of the bike infrastructure in the study area was medium comfort (39%), which includes multi-use paths, yet these formed a small proportion of the incident hotspots (3–13%). Suggested

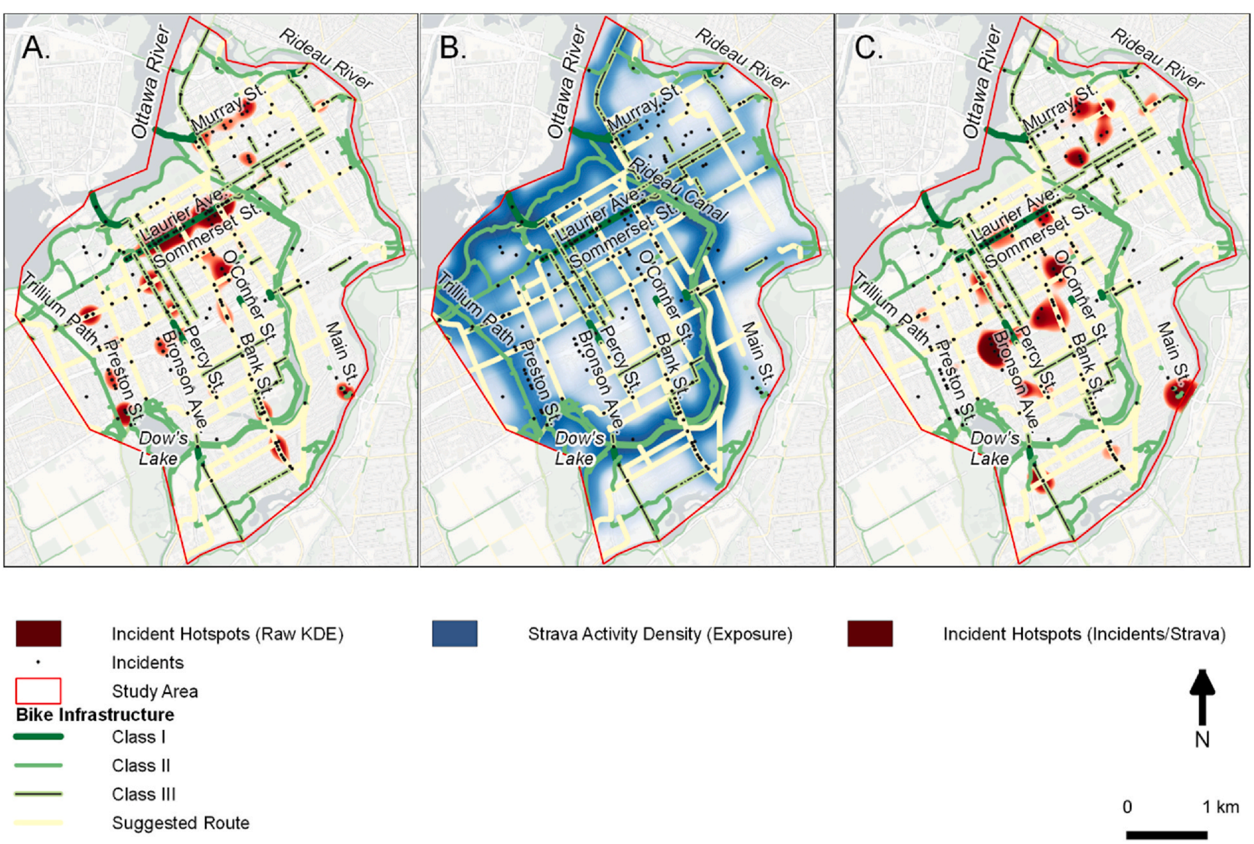

Fig. 1. All incidents and all Strava activities 2015–2016 A) raw incident hotspots, B) exposure (Strava activity density), and C) normalized incident hotspots (incidents/Strava).

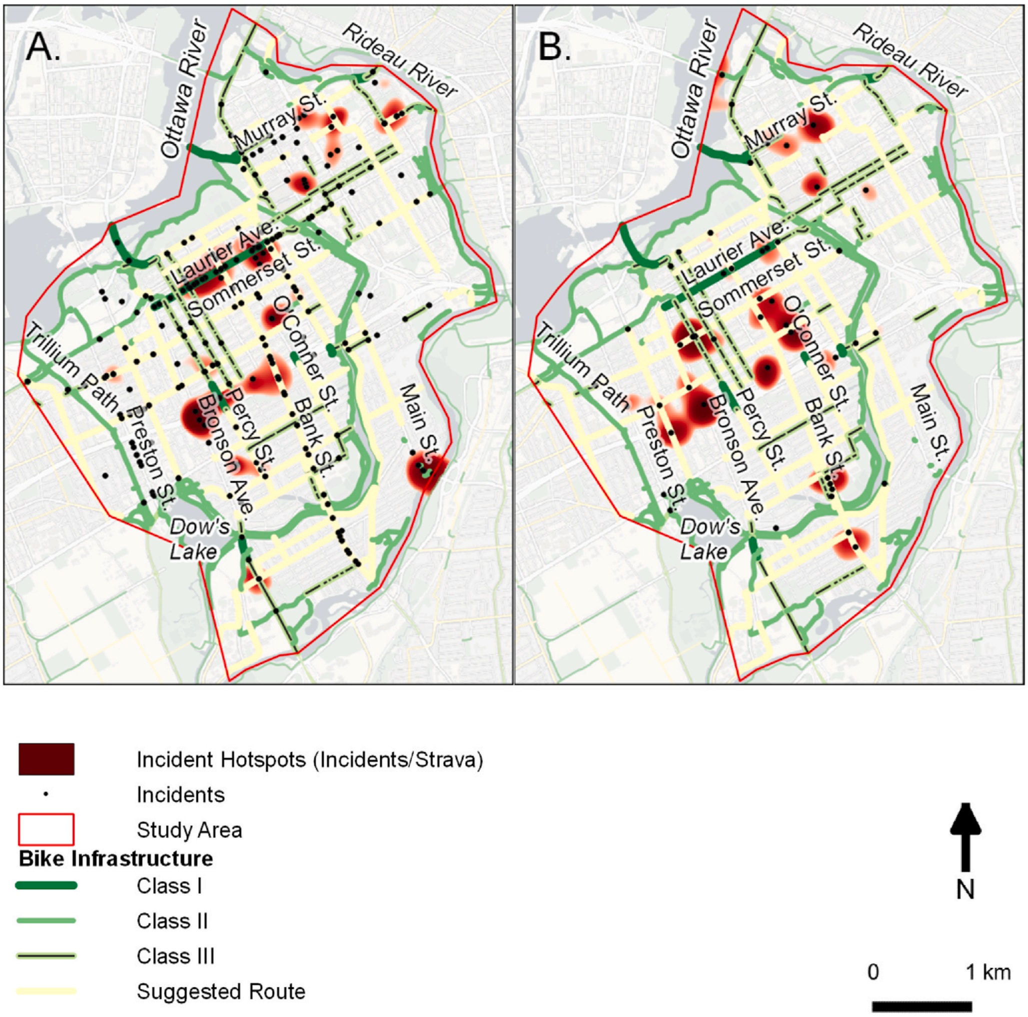

Fig. 2. Normalized incident hotspots for A) business days and B) weekends and holidays.

routes were also very common in the study area (42%), and these comprised an even larger proportion of the incident hotspots (44–69%). Compared to the other timeframes, the normalized incident hotspots for the PM peak commute period had a higher proportion of streets with speed limits above 50 km/h.

4. Discussion

Bicycling safety studies require data on the number of bicyclists in order to quantify exposure and characterize safety (Lovegrove & Litman, 2008; Osama & Sayed, 2017; Prato et al., 2016). The challenges in mapping bicycling exposure has limited bicycling safety studies, as few cities have spatially and temporally detailed ridership data. Estimating site-specific city-wide bicycle counts using traditional counts requires modeling based on informed assumptions, for example 1) searching for measurements on similar infrastructure types, on similar weekdays, and at similar times of the year, 2) calculating expansion factors, and 3) scaling counts to reflect weather and broader trends in ridership (El Esawey, Lim, & Sayed, 2015). In addition to the shortage of available counter data, the time and expertise required to access, assemble, format, and quality-check counter data and then apply models is a barrier to their use. Where count models are not available, Strava data can help provide bicycling exposure data to provide context and aid in interpretation for safety studies. Strava provides several advantages over traditional count data in that it is spatially and temporally continuous (including locations outside of the official bike network) and detailed. High resolution bicycling ridership data will transform our ability to represent exposure and study safety.

Strava data provide an unprecedented opportunity to map exposure in safety studies at a very high spatial and temporal resolution. Strava is both spatially and temporally continuous, making it possible to match exposure to the location and time period of the safety data. In Ottawa, there are 12 automated counters located on multi-use paths (eight), and separated bike lanes (four), with counts available through open data at a daily resolution. Yet Strava provides counts for 3632 roads and paths in the study area with 1-min resolution, making it possible to understand the patterns of ridership between and beyond the automated counters. Raw incident hotspots were in the downtown core (i.e. on Laurier Avenue); however, when the incident hotspots were normalized for exposure (using Strava data), the locations shifted away from the protected bike lanes in the downtown core. Instead, the largest incident hotspots – when normalized for exposure - were on commercial streets outside of the downtown core. This type of analysis may suggest priority locations for increasing the connectivity of safe bicycling networks. We recommend that researchers, planners, and public health practitioners consider the complementary information from both raw and normalized hotspot maps, to capture both burden and risk in prioritizing the locations for safety improvements.

Representation is an important consideration in using crowdsourced data, since Strava data best represent the people who use the app the most (Haklay, 2016), and different apps can attract users with particular bicycling behaviors (Watkins, Ammanamanchi, LaMondia, & Le Dantec,

Fig. 3. Normalized incident hotspots for A) morning peak commute period (7–9 am), B) afternoon peak commute period (3–6 pm), and C) all other times on business days.

Table 3
Summary of road infrastructure within the full study area compared to within hotspots calculated as the length (km) and percent in each category.

Variable	Study area total	Hotspots (top 10% of the KDE)						
	All infrastructure	Overall (Non-normalized)	Overall (normalized)	Business day (full day, normalized)	Weekend or holiday (all, normalized)	AM Peak	PM Peak	Non-commute times on business day
Car and truck infrastructure								
Speed limit≥50 km/h	121.2 71%	25.9 86%	19.8 81%	21.8 86%	18.2 74%	19.0 81%	20.3 87%	18.0 82%
Bike infrastructure (Can-BICS classification) and suggested bike routes								
I. High comfort	3.5 16%	1.9 13%	1.0 13%	1.4 16%	0.5 6%	1.4 15%	1.1 12%	0.7 8%
II. Medium comfort	41.1 39%	1.9 13%	0.6 8%	0.6 6%	0.2 3%	1.2 13%	0.5 5%	0.8 9%
III. Low comfort	17.5 16%	3.5 24%	1.5 19%	2.1 24%	1.8 22%	2.5 27%	2.1 23%	1.9 21%
Suggested routes	44.3 42%	7.3 50%	4.7 61%	4.7 54%	5.6 69%	4.0 44%	5.6 60%	5.5 62%

2016). One unique consideration for the representation of Strava data in Ottawa, is that bike advocacy groups campaigned to encourage "regular commuters to use it to map their journeys to the library, the grocery store and other mundane, everyday trips" (Pritchard, 2016), which may increase the diversity of trips captured on Strava. Strava reports that of the >10,000 Strava accounts in Ottawa in 2016, 78% are men, and 60% of trips were commuting. In contrast, 64% of people in Ottawa who bicycle as a primary mode of transportation to work are men (Statistics Canada, 2019). While (as elsewhere), Strava contributors are disproportionately men; our comparisons with counter data suggest spatio-temporal patterns generally reflect the cycling population. Even in cities without data collection campaigns, researchers have shown that in urban areas Strava data represent broader patterns of bicycling (Jestico et al., 2016; Roy et al., 2019; Sanders, Frackelton, Gardner, Schneider, & Hintze, 2017).

The Strava data demonstrated high exposure on weekends and holidays (more than six million activities) and on multi-use paths, times and places when there were in fact very few cycling safety incidents. Research shows that safety on multi-use paths is often over-estimated by bicyclists, and incidents are under-reported (since the incidents often don't involve cars) (Jestico, Nelson, Potter, & Winters, 2017). We included crowdsourced incident data from BikeMaps.org, which includes more crashes on bike infrastructure than official sources (Branion-Calles, Nelson, & Winters, 2017), but there were still very few incidents reported on multi-use paths. Additionally, the multi-use paths include road crossings where there is potential for collisions with cars that may be recorded in official records (Jestico et al., 2017). Given the low incident rate, our results suggest that these are relatively safe times and places to ride bikes in Ottawa. For individuals planning routes, our results suggest that the Strava Heatmap (https://www.strava.com/heatmap) may be useful for finding safe routes.

Higher incident rates on business days may be related to time- and location-based constraints on travel patterns (work obligations), and higher exposure to automobiles (more car trips). Our analyses showed that during peak commute times, incident hotspots corresponded with areas with high comfort bike infrastructure. This suggests that high comfort bike infrastructure primarily serves commuting riders. These hotspots, for example, along the eastern portion of Laurier Avenue corresponded with locations identified for engineering study in a report prepared for the City of Ottawa in 2011 (Delphi MRC, 2011). Outside of commute hours and on weekends, hotspots occurred outside the city center, especially on commercial streets. Recreational riders on weekends may be able to choose safe routes on multi-use paths (where there were few incident hotspots), but other types of bicycling related to amenities such as shopping or social venues may explain the incident hotspots on commercial streets. Sometimes business owners oppose building protected bike infrastructure on these types of locations due to a perceived impact on customers through loss of parking (Wild, Woodward, Field, & Macmillan, 2018). Our results suggest that commercial streets in Ottawa are priority locations for bicycling safety interventions. The hotspots for all timeframes had a higher proportion (74–86%) of streets with speed limits greater than 50 km/h compared to the larger study area. The hotspot maps may provide a way of identifying locations for traffic calming measures or building higher comfort bike infrastructure to improve bike safety.

The approach demonstrated here is unique in that it uses a KDE estimate for bicycling exposure. Hotspot maps are density estimates, rather than discrete counts. Studies that use KDE often discuss bicycling exposure in the interpretation of the results (Boss et al., 2018). A limitation of this approach is that KDE were calculated using Euclidian distance (i.e. planar KDE), while actual travel on streets and paths is constrained to network geometry. This limitation can cause bias at fine spatial scales (Okabe, Satoh, & Sugihara, 2009). The results presented here are indicative of the broad-scale patterns evaluated in this manuscript, and we are working towards developing network-based KDEs for research at finer spatial scales. Exposure from motorized vehicles is a primary determinant of safety for incidents involving motorized vehicles (Lovegrove & Litman, 2008; Osama & Sayed, 2017; Prato et al., 2016). For example, Harirforoush and Bellalite (2019) included exposure from motorized vehicles in a secondary modeling step within network KDE hotspots. The incidents in winter were spatially dispersed and we were not able to create meaningful hotspot maps, but the data were still useful for calculating and comparing incident rates. Bike incidents are under-reported in official data (Winters & Branion-Calles, 2017). We encourage researchers, planners, and public health practitioners to critically consider representation and reporting limitations in both crowdsourced and official data sources alike.

5. Conclusions

Exposure matters. Intuitively, safety analysts understand that exposure is critical to robust results. These results add evidence to the need for exposure studies and also provide an approach for mapping exposure. Strava can provide extensive count data, including patterns of bicyclist behavior by season, day, and time of day. Normalizing incident hotspot maps using exposure from Strava data moved incident hotspots away from protected bike infrastructure. Normalized incident hotspot maps identified commercial streets as priority locations for bike safety interventions. We found support for safety riding multi-use paths on weekends and holidays. Raw and normalized incident hotspot maps provided complimentary information about bike safety burden and risk in the city of Ottawa. City planners and public health practitioners can consider the spatial and temporal patterns of bicycling exposure for prioritizing locations for safety improvement in cities.

Author statement

Colin Ferster: Methodology, Data Curation, Software, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, and Visualization. **Trisalyn Nelson:** Conceptualization, Methodology, Supervision, Writing - Original Draft, Writing - Review & Editing, and Funding acquisition. **Karen Laberee:** Methodology, Data Curation, Writing - Original Draft, Writing - Review & Editing, Project administration, and Funding acquisition. **Meghan Winters:** Writing - Review & Editing, Resources, and Funding acquisition.

Declaration of competing interest

The authors declare no conflict of interest.

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References

Baddeley, A., & Turner, R. (2005). spatstat: An R package for analyzing spatial point patterns. *Journal of Statistical Software, 12*(6), 1–42. https://doi.org/10.18637/jss.v012.i06

Beck, L. F., Dellinger, A. M., & O'Neil, M. E. (2007). Motor vehicle crash injury rates by mode of travel, United States: Using exposure-based methods to quantify differences. *American Journal of Epidemiology, 166*(2), 212–218. https://doi.org/10.1093/aje/kwm064

Bíl, M., Andrášik, R., & Sedoník, J. (2019). A detailed spatiotemporal analysis of traffic crash hotspots. *Applied Geography, 107*(May), 82–90. https://doi.org/10.1016/j.apgeog.2019.04.008

Boss, D., Nelson, T., & Winters, M. (2018). Monitoring city wide patterns of cycling safety. *Accident Analysis & Prevention, 111*, 101–108. https://doi.org/10.1016/j.aap.2017.11.008. June 2017.

Branion-Calles, M., Nelson, T., & Winters, M. (2017). Comparing crowdsourced near-miss and collision cycling data and official bike safety reporting. *Transportation Research Record: Journal of the Transportation Research Board, 2662*(1), 1–11. https://doi.org/10.3141/2662-01

Conrow, L., Wentz, E., Nelson, T., & Pettit, C. (2018). Comparing spatial patterns of crowdsourced and conventional bicycling datasets. *Applied Geography, 92*(October 2017), 21–30. https://doi.org/10.1016/j.apgeog.2018.01.009

Delphi, M. R. C. (2011). Ottawa cycling safety study report. Ottawa, ON. Retrieved from https://app06.ottawa.ca/calendar/ottawa/citycouncil/trc/2011/06-29/05 - Ottawa Cycling Safety Study Report_Issued.pdf.

El Esawey, M., Lim, C., & Sayed, T. (2015). Development of a cycling data model: City of vancouver case study. *Canadian Journal of Civil Engineering, 42*(12), 1000–1010. https://doi.org/10.1139/cjce-2015-0065

Government of Canada. (2019). Canadian climate normals 1981-2010 station data. Retrieved July 12, 2019, from http://climate.weather.gc.ca/climate_normals/.

Griffin, G., Nordback, K., Götschi, T., Stolz, E., & Kothuri, S. (2014). Monitoring bicyclist and pedestrian travel and behavior, current research and practice. Washington D.C. Retrieved from http://onlinepubs.trb.org/onlinepubs/circulars/ec183.pdf.

Haklay, M. (2016). Why is participation inequality important? In C. Capineri, M. Haklay, H. Huang, V. Antoniou, J. Kettunen, F. Ostermann, et al. (Eds.), *European handbook of crowdsourced geographic information* (pp. 35–44). London: Ubiquity Press. https://doi.org/10.5334/bax.

Harirforoush, H., & Bellalite, L. (2019). A new integrated GIS-based analysis to detect hotspots: A case study of the city of sherbrooke. *Accident Analysis & Prevention, 130*, 62–74. https://doi.org/10.1016/j.aap.2016.08.015

Hijmans, R. J. (2019). raster: Geographic data analysis and modeling. Retrieved from https://cran.r-project.org/package=raster.

Jestico, B., Nelson, T. A., Potter, J., & Winters, M. (2017). Multiuse trail intersection safety analysis: A crowdsourced data perspective. *Accident Analysis & Prevention, 103*, 65–71. https://doi.org/10.1016/j.aap.2017.03.024

Jestico, B., Nelson, T., & Winters, M. (2016). Mapping ridership using crowdsourced cycling data. *JTRG, 52*, 90–97. https://doi.org/10.1016/j.jtrangeo.2016.03.006

Kweon, Y. J., & Kockelman, K. M. (2003). Overall injury risk to different drivers: Combining exposure, frequency, and severity models. *Accident Analysis & Prevention, 35*(4), 441–450. https://doi.org/10.1016/S0001-4575(02)00021-0

Lovegrove, G. R., & Litman, T. (2008). Using macro-level collision prediction models to evaluate the road safety effects of mobility management strategies: New empirical

tools to promote sustainable development. In *87th transportation research board annual meeting* (Vol. 4165, p. 24).
Nelson, T. A., Denouden, T., Jestico, B., Laberee, K., & Winters, M. (2015). BikeMaps.org: A global tool for collision and near miss mapping. *Frontiers in Public Health, 3* (March), 1–8. https://doi.org/10.3389/fpubh.2015.00053
Okabe, A., Satoh, T., & Sugihara, K. (2009). A kernel density estimation method for networks, its computational method and a GIS-based tool. *International Journal of Geographical Information Science, 23*(1), 7–32. https://doi.org/10.1080/13658810802475491
OpenStreetMap Contributors. (2019). OpenStreetMap. Retrieved June 6, 2019, from https://www.openstreetmap.org.
Osama, A., & Sayed, T. (2017). Evaluating the impact of socioeconomics, land use, built environment, and road facility on cyclist safety. *Transportation Research Record, 2659* (2659), 33–42. https://doi.org/10.3141/2659-04
Prato, C. G., Kaplan, S., Rasmussen, T. K., & Hels, T. (2016). Infrastructure and spatial effects on the frequency of cyclist-motorist collisions in the Copenhagen Region. *Journal of Transportation Safety & Security, 8*(4), 346–360. https://doi.org/10.1080/19439962.2015.1055414
Pritchard, T. (2016, April 22). *Ottawa-Gatineau cyclists urged to map their journeys*. CBC News Ottawa. Retrieved from https://www.cbc.ca/news/canada/ottawa/strava-app-ottawa-1.3546513.
Rodgers, G. B. (1995). Bicyclist deaths and fatality risk patterns. *Accident Analysis & Prevention, 27*(2), 215–223. https://doi.org/10.1016/0001-4575(94)00063-R
Roy, A., Nelson, T. A., Fotheringham, A. S., & Winters, M. (2019). Correcting bias in crowdsourced data to map bicycle ridership of all bicyclists. *Urban Science, 3*(2), 62. https://doi.org/10.3390/urbansci3020062
Sanders, R. L., Frackelton, A., Gardner, S., Schneider, R., & Hintze, M. (2017). " ballpark " method for estimating pedestrian & bicyclist exposure in Seattle : A potential option for resource-constrained cities in an age of big data. *Transportation Research Board 96th Annual Meeting, 1–25*.
Statistics Canada. (2019). Census profile, 2016 census: Ottawa, census division [census division]. Ontario. Retrieved July 31, 2019, from https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/page.cfm?Lang=E&Geo1=CSD&Code1=3506008&Geo2=CD&Code2=3506&SearchText=Ottawa&SearchType=Begins&SearchPR=01&B1=All&TABID=1&type=0.
Vanparijs, J., Int Panis, L., Meeusen, R., & De Geus, B. (2015). Exposure measurement in bicycle safety analysis: A review of the literature. *Accident Analysis & Prevention, 84*, 9–19. https://doi.org/10.1016/j.aap.2015.08.007
Watkins, K., Ammanamanchi, R., LaMondia, J., & Le Dantec, C. A. (2016). Comparison of smartphone-based cyclist GPS data sources. In *Transportation research board 95th annual meeting* (Vols. 16–5309).
Wild, K., Woodward, A., Field, A., & Macmillan, A. (2018). Beyond 'bikelash': Engaging with community opposition to cycle lanes. *Mobilities, 13*(4), 505–519. https://doi.org/10.1080/17450101.2017.1408950
Winters, M., & Branion-Calles, M. (2017). Cycling safety: Quantifying the under reporting of cycling incidents in Vancouver, British Columbia. *Journal of Transport and Health, 7*, 48–53. https://doi.org/10.1016/j.jth.2017.02.010
Winters, M., Zanotto, M., & Butler, G. (2020). The canadian bikeway comfort and safety (Can-bics) classification system: A common naming convention for cycling infrastructure. *Health Promotion and Chronic Disease Prevention in Canada, 40*(9), 288–293. https://doi.org/10.24095/hpcdp.40.9.04