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Using crowdsourced data to monitor change in spatial patterns of bicycle ridership

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ABSTRACT

Cycling is a sustainable mode of transportation with numerous health, environmental and social benefits. Investments in cycling specific infrastructure are being made with the goal of increasing ridership and population health benefits. New infrastructure has the potential to impact the upgraded corridor as well as nearby street segments and cycling patterns across the city. Evaluation of the impact of new infrastructure is often limited to manual or automated counts of cyclists before and after construction, or to aggregate statistics for a large region. Due to methodological limitations and a lack of data, few spatially explicit approaches have been applied to evaluate how patterns of ridership change following investment in cycling infrastructure. Our goal is to demonstrate spatial analysis methods that can be applied to emerging sources of crowdsourced cycling data to monitor changes in the spatial-temporal distribution of cyclists across a city. Specifically, we use crowdsourced ridership data from Strava to examine changes in the spatial-temporal distribution of cyclists in Ottawa-Gatineau, Canada, using local indicators of spatial autocorrelation. Strava samples of bicyclists were correlated with automated counts at 11 locations and correlations ranged from 0.76 to 0.96. Using a local indicator of spatial autocorrelation, implemented on a network, we applied a threshold of change to separate noise from patterns of change that are unexpected given a null hypothesis that processes are random. Our results indicate that the installation or temporary closure of cycling infrastructure can be detected in patterns of Strava sample bicyclists and changes in one location impact flow and relative volume of cyclists at multiple locations in the city. City planners, public health professionals, and researchers can use spatial patterns of Strava sampled bicyclists to monitor city-wide changes in ridership patterns following investment in cycling infrastructure or other transportation network change.

1. Introduction

Cycling is a sustainable mode of transportation with numerous health, environmental and social benefits (Gordon-Larsen et al., 2005; Pucher and Buehler, 2008; Teschke et al., 2012). In an effort to increase ridership, many cities are making significant financial investments in cycling infrastructure, and several cities are developing cycling infrastructure networks (Buehler and Dill, 2015). It is essential that cities monitor and report on the impact of infrastructure projects on ridership to be accountable to the public and to

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encourage political will for future investments in cycling infrastructure (Handy et al., 2014).

Monitoring and evaluation of the impacts of investment in cycling infrastructure across a city have been difficult due to a lack of spatially explicit ridership data. Traditional sources of cycling data and route information include manual counts, intercept surveys, automated pneumatic tube counters, mail-back surveys, travel surveys, and research projects (Forsyth et al., 2010; Hyde-Wright et al., 2014; Nordback et al., 2013). While traditional cycling data provide important information on bicycling levels, standard data lack the spatial and temporal detailed needed for mapping change in bicycling levels. Data limitations are being overcome through advances in Global Positioning System (GPS) technology and its incorporation into portable devices, such as smartphones, which provides a novel source of spatially and temporally dense cycling data. Further, large citizen science cycling datasets are becoming available for analysis (Romanillos et al., 2015). For example, in North American cities, crowdsourced cycling data has been used to examine where cycling for health occurs with respect to land use diversity, bicycle facilities and residential and employment density (Griffin and Jiao, 2015) and researchers have observed a strong correlation between crowdsourced fitness app data and manual cycling counts (Jestico et al., 2016).

In order to utilize crowdsource data for monitoring ridership change we must identify suitable analytical methods. Spatial statistics enable spatial patterns in data to be mapped and unusual patterns identified (Nelson and Boots 2008). When mapping change, it is essential to differentiate minor and random change from substantive change. A group of spatial statistics, local measures of spatial autocorrelation, can be used to quantify relatedness in nearby events and to map when and where patterns are statistically associated with non-random spatial processes (Anselin 1995). Specifically Local Moran's I_i is used to map clusters of extreme change.

Our goal is to demonstrate how spatial pattern methods can be applied to crowdsourced ridership data to monitor changes in the spatial-temporal variation of ridership across a city. We analyzed a large crowdsourced cycling dataset for Ottawa-Gatineau, Canada, comparing volumes of cyclists from May 2015 and May 2016 to meet the following objectives. First, we evaluate the appropriateness of using crowdsource data to represent bicycling levels. Second, we quantified change in patterns of ridership using network appropriate measures of local spatial autocorrelation. Third, we tracked changes associated with three bicycling infrastructure projects that occurred over the time period of our study.

2. Study area and data

2.1. Study area

The case study area is Ottawa-Gatineau, Canada with a population of 1.24 million (Statistics Canada, 2011a). Approximately 2.2% of workers commute by bicycle (Statistics Canada, 2011b). From 2006 to 2011 daily bicycle trips grew from 30,350 to 43,350 (an increase of 43%) (City of Ottawa 2013). The region has invested significant financial resources in bicycle and multi-use infrastructure over the past several years and currently has over 600 km of bicycle paths (National Capital Commission, 2017). Infrastructure that we monitor for change in ridership patterns: are Adawe bike and pedestrian bridge (opened December 2015), Hickory bike and pedestrian bridge (opened August 2015), MacDonald-Cartier pathway (opened December 2015).

2.2. Official Bicycling Data

Ottawa-Gatineau had 10 bicycling counters in 2015 and 11 in 2016 and we utilized bicycle counts on weekdays (24-h days) in May for 2015 and 2016. Bicycling counters are automated counters located throughout the city. Data are reported daily and counters are considered accurate within +0 and –5% of bikes that cross the sensing section of the pathway. Data are accessed from an open data portal managed by the City of Ottawa. We compare official data with crowdsourced data described below.

2.3. Crowdsourced Bicycling Data

The City of Ottawa has partnered with Strava, a social network for runners and cyclists, to obtain a large crowdsourced cycling dataset. The Strava mobile App is used by athletes to track their activities which are then uploaded to the Strava website. This volunteer sourced data is anonymized and aggregated into the Strava Metro data product (Strava Metro, 2017). The Strava Metro data used in this study consists of activity counts (bicycle trips) per segment of transportation infrastructure in the Ottawa-Gatineau region, aggregated by month using weekday data in May 2015 and May 2016. We chose this time period as several substantial changes were made to cycling infrastructure between May 2015 and 2016, and thus this serves as a pre-post analysis. There were a total of 4.49 million activity counts from 52,123 bike trips across 71,205 network segments. Strava is used most commonly by recreational cyclists but in dense urban areas correlates with all bicyclists (Jestico et al. 2016). In Ottawa-Gatineau we expect a higher proportion of commuters than typical in Strava data due to a marketing campaign led by the city for commuters to contribute data to Strava in advance of the data purchase. The street segment map included in the Strava Metro data product was derived from OpenStreetMap (OpenStreetMap, 2017).

The demographics of the Strava users in Ottawa-Gatineau are not representative of the general cycling population, there are differences in both gender and age. The percentage of male Strava users (78.2%) is higher than the percentage of male cyclists in the Ottawa-Gatineau region (68%) (TRANS Committee, 2011). Strava users in the 25–34 and 35–44 age groupings are over-represented as compared to the actual cycling population, while the under 25, 55–64, 65–74 and over 75 age groupings of Strava users are under-represented (Fig. 1). The trends in the Strava data used in this study are very similar to age and gender trends of crowdsourced data used in other bicycling studies (i.e., Griffin and Jiao 2015; Romanillos et al. 2016).

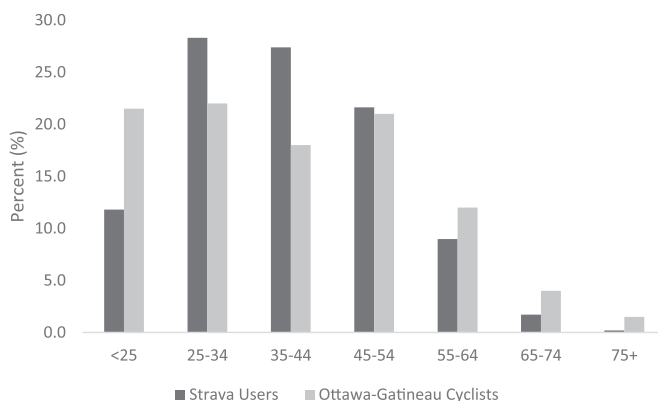


Fig. 1. Strava users versus cycling population by age in Ottawa-Gatineau (TRANS Committee, 2011).

3. Methods

3.1. Comparing Strava and official counts

Strava is a large and detailed sample of bicyclists, but it oversamples men and fitness riders and under samples children, women, and novice bicyclists. To determine if it is appropriate to use Strava to monitor city wide ridership in Ottawa-Gatineau we correlated Strava and official counts of ridership at 11 locations throughout Ottawa using simple linear regression.

3.2. Spatial pattern of change in city-wide ridership

To map change in ridership along each segment we first summed the total of all activity counts across the study area for each time period, and then calculated a normalized ridership value for each segment, representing the proportion of all activity counts that occurred within that time period on each segment. We subtracted the normalized ridership in May 2015 from May 2016 on a segment-by-segment basis and created a map of the absolute difference. We visualized the resulting data on a map in an attempt to identify change in the spatial variation of bicycle trips.

We used a spatial statistic that measures autocorrelation to identify where changes in ridership occurred that were unexpected based on a null hypothesis of random change. Spatial autocorrelation is the concept that all things are related, but things near to one another are more related than things far apart (Tobler, 1965). Positive spatial autocorrelation, often described as a cluster, is present when the value of a variable at a location is similar to values of the same variable at locations close by. Negative spatial autocorrelation, often described as an outlier, is present when the values of a variable at nearby locations are dissimilar. When applied to bicycling ridership change, positive spatial autocorrelation are clusters of streets with statistically increased or decreased ridership and negative spatial autocorrelation identifies a street segment that has experience a change that is different than the surrounding streets.

Local Moran's I_i is a common measure of spatial autocorrelation and is useful for identifying spatial autocorrelation in values that are high or low relative to the mean. By focusing on high and low values, Moran's I is helpful for identifying where positive and negative changes in bicycling levels cluster.

Local Moran's I_i is calculated as:

$$I_i = \frac{n(x_i - \bar{x}) \sum_j w_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2},$$

where n is the number of regions, x_i is the variable value at region i for $i = (1, \dots, n)$, x_j is the variable value at neighboring region j for $j = (1, \dots, n)$, \bar{x} is the average of variable x across the study area, and w_{ij} is the i th - j th element of a weight matrix W designating the spatial relationship between regions i and j (Anselin, 1995).

It is worth noting that like most spatial pattern statistics, local Moran's I_i is typically implemented on a two-dimensional surface; however, our study area consists of transportation infrastructure which occupies network space. We based our spatial weights matrix on the contiguity of infrastructure segments or a network. Every segment has two nodes that represent either an intersection or the end of a segment. We implemented a binary adjacency matrix where $w_{ij} = 1$ for regions that are adjacent, otherwise $w_{ij} = 0$. To expand the size of the neighborhood of i , the neighbors of j can be added to the neighborhood of i . This process can be iterated to generate multiple neighborhood sizes (lags). We calculated local Moran's I_i using a first order lag neighborhood and the difference in normalized ridership between May 2015 and 2016 (Fig. 2).

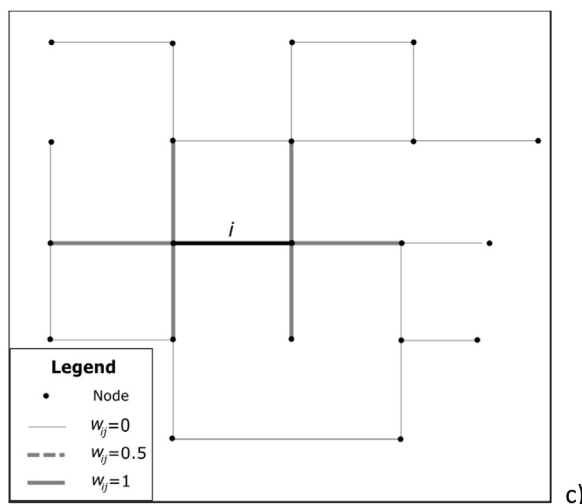


Fig. 2. Definitions of spatial weights matrices for segment i : first order lag, equal weighting with $w_{ij} = 1$ for contiguous street segments.

3.3. Relating changes in ridership to changes in infrastructure

We compared the detected change in ridership with the location of three infrastructure projects in Ottawa-Gatineau: Adawe bike and pedestrian bridge, MacDonald-Cartier pathway, and Hickory bike and pedestrian bridge. As the entire city is monitored using this method, many changes in bicycling levels are mapped and city staff contextualized the change by identifying infrastructure changes pertaining to cycling during 2015 and 2016.

4. Results

4.1. Comparing Strava and official counts

The linear correlations between the Strava sampled ridership and official counts of all bicyclists were high and ranged from 0.76 to 0.96 (Table 1). In 2016 when Ottawa-Gatineau had a campaign to encourage bicyclists to map their trips on Strava correlations were 0.86 or higher.

4.2. Spatial pattern of change in city-wide ridership

The map of the absolute difference in normalized ridership between May 2015 and May 2016 is presented in Fig. 3. We were able to identify network segments where normalized ridership increased or decreased, but it was not possible to determine if the observed changes were due to chance or to identify where statistically significant network clustering was present in the variation in ridership.

In Fig. 4 we show the results of local Moran's I_i on the difference in normalized ridership between May 2015 and 2016. The map of local Moran's I_i results can be used to identify street segments where change in the spatial pattern of ridership is statistically different than expected based on random processes. In these locations ridership changes that is extreme, relative to mean, are either

Table 1
Official counts correlated with Strava counts for 11 locations across Ottawa-Gatineau.

Station	Name	Correlation	
		2015	2016
1	Alexandra Bridge Bikeway	0.93	0.96
2	Ottawa River Pathway	0.96	0.91
3	Eastern Canal Pathway	0.88	0.91
4	Western Canal Pathway	0.88	0.86
5	Laurier West of Metcalfe	0.83	0.93
6	Laurier East of Lyon	0.84	0.91
7	Somerset Bridge	0.76	0.90
8	O-Train north of Young St.	0.90	0.95
9	O-Train north of Gladstone Ave	0.93	0.95
10	O-Train north of Bayview	0.89	0.93
11	Adawe Crossing	NA	0.93

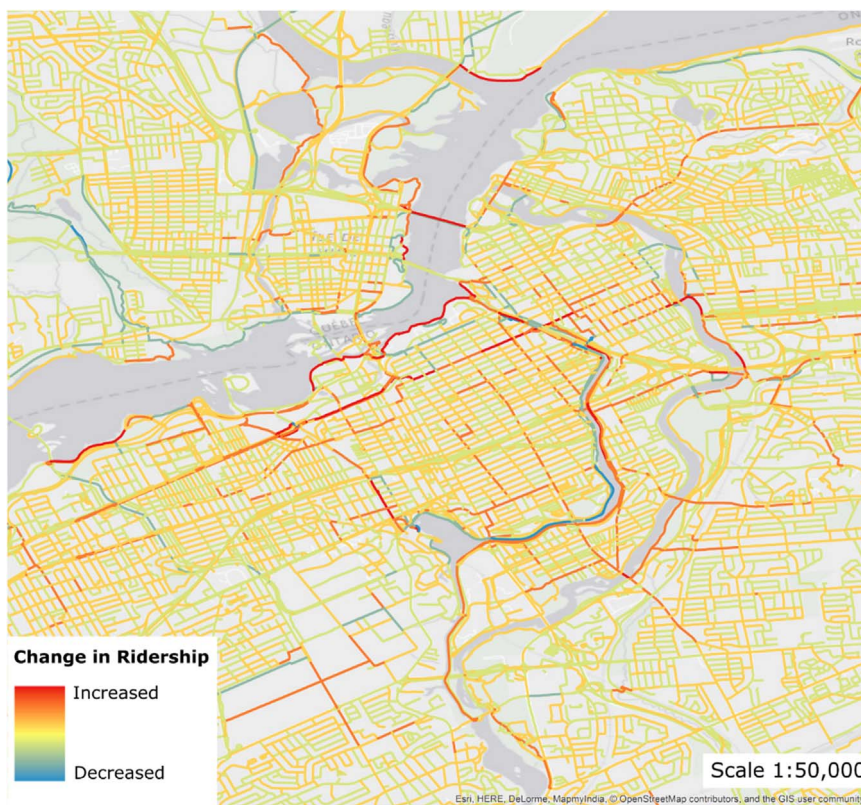


Fig. 3. Change in relative volume of ridership, May 2015 to May 2016.

unexpectedly clustered (i.e., a group of street segments show extreme increases or decreases in bicycling) or isolated (i.e., a single street segment that has extreme increased or decreased ridership surrounded by a street with less change). Generally, there is clustering of increased cycling in the Northwest portion of the city. While below the Ottawa River there are several clusters of increased bicycling. Outliers of change occur throughout the city.

4.3. Relating changes in ridership to changes in infrastructure

Interpretations of changes associated with major infrastructure projects are visualized in Fig. 5. Adawe bicycle and pedestrian bridge shows increased ridership on the new bridge and change in bicycling patterns on related routes (Fig. 5a). There was no bridge to sample bicyclists on in 2015 and May 2016 Strava ridership measured 964 riders. As bicyclist moved to the new bridge, the roadways to the west saw increased bicycling traffic. To the north, a less desirable bridge which is share with vehicles became saw lower bicycling levels as bicyclist's likely shifted their route onto the new protected route. Installation of the Hickory bicycle and pedestrian bridge lead to increased bicycling on and around the new infrastructure (Fig. 5b). In May 2016 83 Strava bicyclists used the Hickory bridge. The installation of the MacDonald-Cartier pathway also lead to changes in bicycling patterns (Fig. 5c). In May 2016 867 Strava bicyclists used the route. Bicyclists shifted onto the new pathway from the vehicle bridges both adjacent and to the south. Beyond the infrastructure being monitored, other changes in the patterns of city-wide bicycling were apparent. In Fig. 5d we show that our methods picked up changes due to a construction project, where bicyclists were r-routed due to a temporary closure of a tunnel.

5. Discussion

The ability of cities to monitor and evaluate the impacts of investment in cycling infrastructure has been limited by a lack of spatially continuous ridership data. In this paper, we demonstrated a spatially explicit approach for monitoring variation in ridership by applying network constrained spatial analysis methods to novel sources of cycling data. We applied this in a real-world example, using autocorrelation analysis on a crowdsourced cycling ridership dataset. In this case study, we were able to detect change associated locations where cycling infrastructure had been installed, could detect shifts in bicycling patterns around infrastructure change, and were able to identify temporary changes associated with construction.

We demonstrated a spatially explicit approach for monitoring variation in the patterns of ridership across a city following changes to cycling infrastructure. Previous studies that evaluate impacts of infrastructure improvements have primarily focused on aspatial

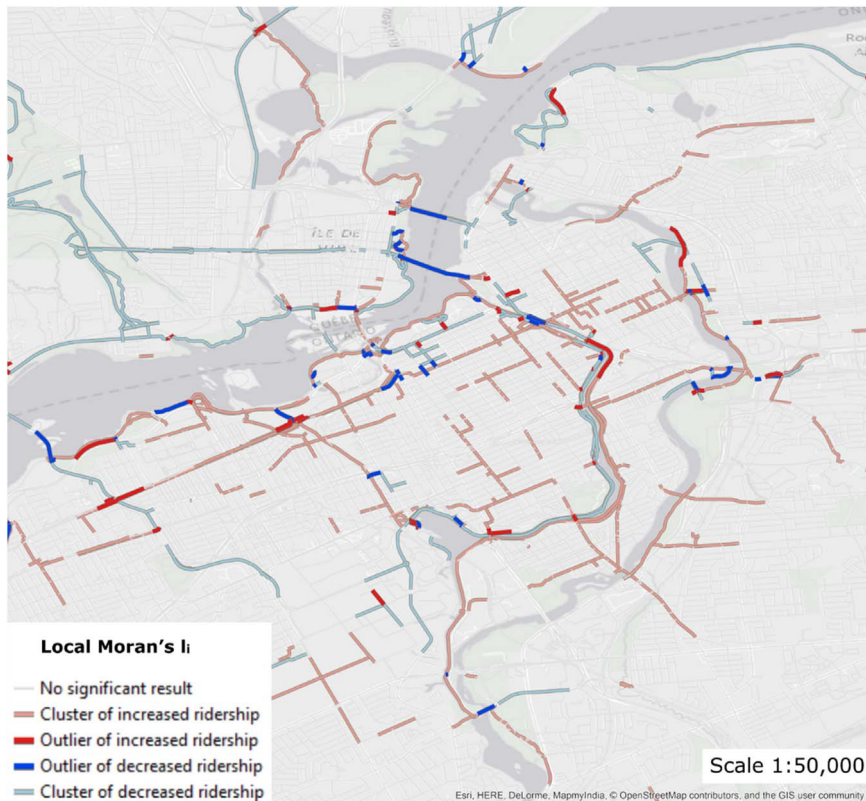


Fig. 4. Network local Moran's I_i of the difference in normalized ridership between May 2015 and May 2016 based on first order neighbors.

methods based on manual or automated cyclist counts on a single street segment. A few studies have performed retrospective analysis that aggregated data on cycling infrastructure and ridership across multiple cities and found positive correlation between cycling facilities and cycle commuting (Buehler and Pucher, 2012), but this approach does not evaluate the impact of a specific change in infrastructure. The results illustrated here demonstrate the importance of considering patterns of change in cycling when infrastructure changes in a city. In the examples of a temporary closures and installation of new infrastructure, change in one location affects the flow and amount of bicycle traffic in multiple locations. Our results suggest cyclists are shifting their routes to take advantage of the new infrastructure. As cities invest more heavily in cycling infrastructure, the need to evaluate how ridership changes is paramount.

Methodologically, the network approach to implement local methods of spatial autocorrelation is an important consideration (Nelson and Boots, 2008). While Local Moran's I_i is commonly run and available in a variety of software, the network version is relatively uncommon. Our code will be available for use in an open format.

From the perspective of practitioners maps of change, like Fig. 4, can be used in a variety of ways. First, the map of change can be intersected with all the constructions and infrastructure projects within a region to quantify the cumulative impact. Second, by evaluating patterns of bicycling ridership change over the entire network practitioners can identify any unexpected changes that need investigation for management of a continuous network. While our approach, using Strava data and spatial pattern statistics, allows mapping of change in the complete network, it also allows evaluation of specific infrastructure projects.

Cycling data collected with GPS enabled devices represent an important source of information that is filling a massive gap in mobility data for active transportation research. GPS cycling data has been used to gain insight into the role of cycling in meeting adults recommended levels of exercise and how this may be impacted by cycling infrastructure (Dill, 2009). Other studies have developed route choice models with GPS data (Broach et al., 2012). These foundation studies had small numbers of participants and gathered data for short time periods. As GPS technology has advanced and been incorporated into smartphones, mobile apps have facilitated the collection of crowdsourced cycling data. This has been picked up for research, for example, Hood et al. (2011) developed a cyclist route choice model for San Francisco, California using GPS data collected from CycleTracks, a smartphone app.

The increase in popularity of health and fitness apps, such as Strava, has provided a novel source of cycling data with high spatial and temporal density. Strava data have been used to examine where cyclists ride (Griffin and Jiao, 2015), and several studies have examined the use of Strava data as a proxy for ridership volumes (Griffin and Jiao, 2015; Jestico et al., 2016). Heesch and Langdon (2016) used heatmaps and counts of cyclists from Strava data to assess the impact of infrastructure change on cycling behavior. In the current study, we advance this field by employing Strava data to monitor spatial patterns of ridership change city-wide, and across time.

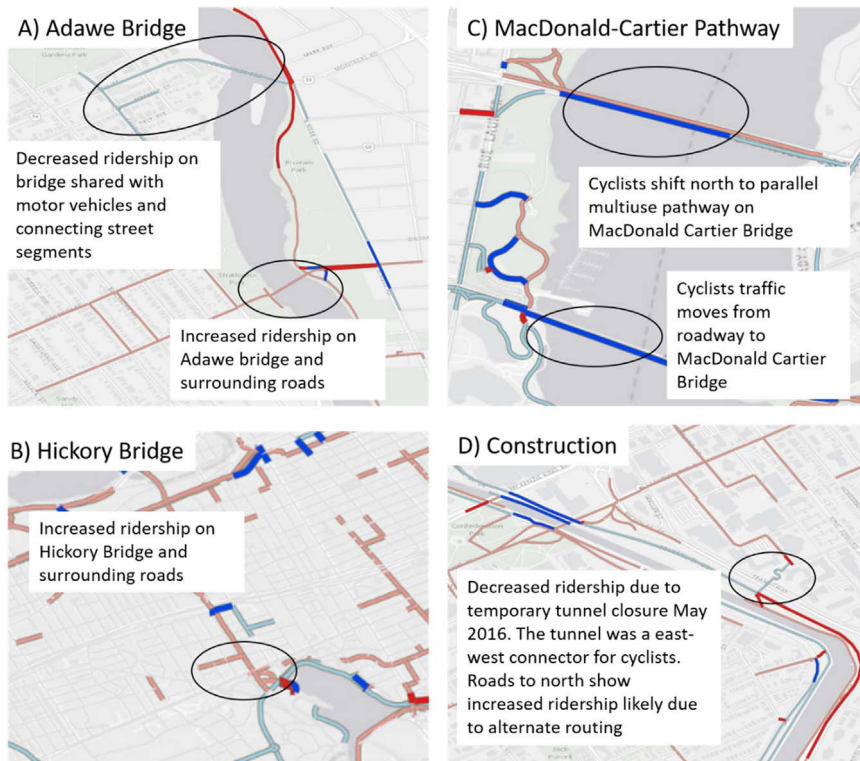


Fig. 5. Interpretations of changes in spatial patterns of ridership in Ottawa-Gatineau. (a) Adawe Bicycle and Pedestrian Bridge shows increased ridership on the new bridge and change in bicycling patterns on related routes. (b) Hickory Bicycle and Pedestrian Bridge lead to increased bicycling on the new infrastructure. (c) MacDonal-Cartier shows that the bridge with vehicles is associated patterns of decreased ridership, while just north increased ridership is mapped. Also changes in ridership patterns are mapped to the south. (d) Though not the focus for change detection the city-wide approach to monitoring picks up several additional changes including construction that resulted in temporary closing of a multiuse tunnel.

While the methods used here are well known to geographers, the application to fitness app data is an important one. A focus on detecting statistically significant change in spatial pattern of ridership is paramount to the successful use of Strava data for transportation planning and research. For example, in another study that used Strava data to evaluate the impact of infrastructure change on cycling behavior, a visual comparison of heat and volume maps pre- and post-infrastructure improvements were helpful, but lacked a method for defining a change threshold (Heesch and Langdon, 2016). Using Local Moran's I_i we can determine when the change in ridership patterns are unexpected based on chance, which is a threshold that can be defended and defined statistically. Using a null hypothesis of random change gives a clear definition of change and in future studies it would be useful to evaluation null models of conditional randomness (Fortin and Jacquez, 2000).

Crowdsourced fitness App data brings new opportunities and challenges for research and practice. However, a unique aspect of fitness App data is that we sample movement across a city. Strava is a large sample of bicycling levels and includes unprecedented spatial and temporal resolution. With millions of users, Strava is an example of how fitness Apps are a growing data source and demonstrating how to effectively convert data into useful information will help fill gaps in cycling data. Like all crowdsourced data, citizen generated ridership data must be used cautiously due to inherent data biases (Feick and Roche, 2013; Ferster et al., 2017). Our results add to the evidence that patterns of Strava riders, correlate with all riders (e.g. correlations ranged from 0.76 to 0.96 between all riders and Strava riders). Strava data over-represent patterns of ridership in middle age males and under-represent younger and older cyclists (Griffin and Jiao, 2015; Heesch and Langdon, 2016; Jestico et al., 2016). In addition to age and gender bias, there is the potential for geographic bias, or varying uptake and use of Strava across a city (Heesch and Langdon, 2016). While bias does exist, Jestico et al. (2016) found a strong correlation between Strava and all riders in the core of a mid-sized North American city. As more cities are purchasing Strava they will not always have the capacity to conduct statistical corrections of data. However, the pattern approach taken in our work is an example of appropriate use of Strava even without bias correction, which is to characterize spatial and temporal patterns in bicycling levels. Planning and research will continue to require official and comprehensive count programs to monitor total number of cyclists, but the logistics of official counts limit spatial coverage.

6. Conclusion

As cities continue to invest limited financial resources in cycling infrastructure, the need to evaluate the impacts on ridership is paramount. Monitoring and evaluation of the impacts of investment in cycling infrastructure across a city have been difficult due to

methodological issues and a lack of spatially explicit ridership data. We have demonstrated how spatial analysis methods can be applied to emerging sources of crowdsourced cycling data to meet this need. Our results demonstrate how change in one location can affect flow and proportion of bicycle traffic at multiple locations. City planners and transportation engineers can use patterns of change in crowdsourced data to monitor changes in ridership patterns following investment in cycling infrastructure or other changes to the transportation network.

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