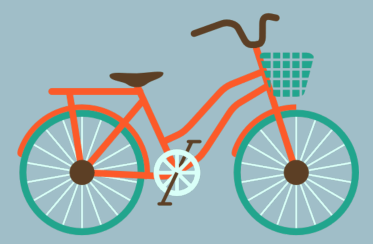
Built Environment Correlates of Bicycling flows in Hamilton, Ontario: Fastest, Quietest, or Balanced Routes?



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Abstract

Bicycling is an increasingly important form of travel for environmental and public health reasons. Although many factors influence bicycling in urban areas, particular attention has been given to the role of the built environment and how specific attributes affect bicycle flows. While information about trip origins and destinations can be inferred from trip records, it is more challenging to capture the attributes of the built environment along specific routes. With new algorithms for cycle routing it is now possible to infer bicycling routes between origins and destinations. Therefore, the objective of this study is to investigate the correlates of bicycling in Hamilton, Ontario, a mid-sized city in Canada and part of the Greater Toronto and Hamilton Area. Using bicycle trip records from the Transportation Tomorrow Survey, a spatial interaction model is developed to test the level of bicycling against various built environment attributes. A feature of the analysis is the use of *CycleStreets* to compare different routes between origins and destinations. The various routes are characterized as being fastest, quietest, or balanced. In addition, network autocorrelation is accounted for in the estimated models. The models suggest that shortest-path quiet routes that allow bicyclists to avoid traffic best explain the pattern of travel by bicycle in Hamilton. This method is useful to better understand the types of routes that bicyclists may seek out and presents opportunities to systematically audit the built environment for attributes that correlate well with bicycling.

1. Introduction

Hamilton is a mid-sized city, located in the Greater Toronto and Hamilton area, which is an urban region in Ontario, Canada. The city has experienced a rise in bicycling in recent years. As of 2016, 1.2% of all trips in Hamilton are made by bicycle according to the latest *Transportation Tomorrow Survey (TTS)*, the periodic travel survey in the region [1]. This represents a two-fold increase from the 2011 survey results. To date, there has been no published research that has investigated bicycle trip trends using the *TTS* data from Hamilton, so we know relatively little about where Hamiltonians are bicycling to and from or the route they potentially use to reach their destination.

Many studies document the relationship between the built environment and bicycling for transport, and identify various attributes that have been found to influence bicycling levels [2-6]. To understand the level and pattern of bicycle trips and to investigate the spatial distribution of such flows at the meso-level, the level of bicycling flows in Hamilton can be tested against various attributes from the known literature.

This study describes the development of a spatial interaction model to test the level of bicycling flows against various built environment attributes. A feature of the analysis is the use of an algorithm for cycle routing, i.e., *CycleStreets* [7], to approximate and compare different routes between origins and destinations. This paper addresses the following two questions: 1) *Which built environment attributes influence bicycle trip flows in Hamilton?*, and 2) *Which type of route best explains the pattern of travel by bicycle in Hamilton?*

2. Data Sources

Secondary data was obtained from the following sources:

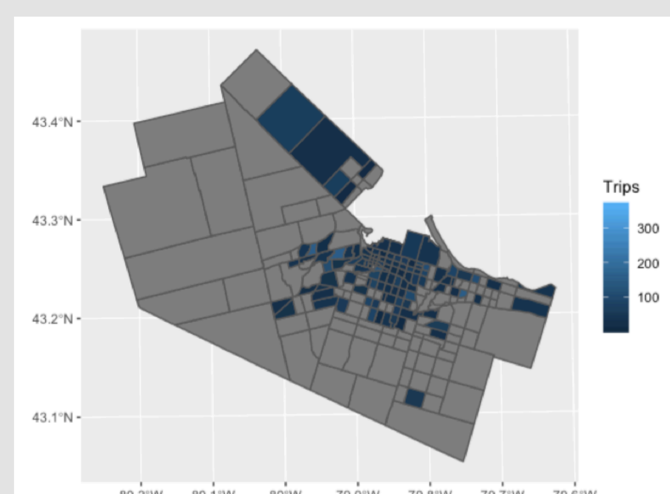
- **University of Toronto Transportation Research Institute:** *Transportation Tomorrow Survey*
- **Statistics Canada:** *2016 Census*
- **DMTI Spatial Inc.:** *Points of Interest*
- **Teranet Inc.:** *Hamilton Parcel/Land Use Data*
- **City of Hamilton Open Data Program:** *Hamilton Street Railway (HSR) Transit Stops*

3. Methods

Data Preparation

A dataframe containing 294 origin-destination (O-D) pairs that produced bicycle trips within Hamilton was accessed. After cleaning and filtering of isolate zones, zonal demographic and built environment attributes that may explain bicycle trip patterns were then added to this table. Although the origin and destination of each trip is known, there is no information available about the routes that were taken by bicyclists who made those trips. To overcome this limitation, a novel feature of the analysis is the use of *CycleStreets*, which can be accessed in R through the package *cyclestreets* to retrieve different routes between origins and destinations that a knowledgeable bicyclist could take [7]. *CycleStreets* characterizes routes as being fastest, quietest, and balanced and each route can be measured by both distance and time, which serves as a measure of spatial separation. A final expanded origin-destination matrix was created with all associated variables for each O-D pair.

Figure 1. Traffic zones in Hamilton that produced bicycle trips.



Spatial Interaction Modelling

Transportation trips, the manifestation of which are flows of people between places, are spatial interactions at the meso-level and can be modelled as such using Poisson regression when the dependent variable is a count [8]. Bicycle trips were recorded as counts in the *TTS*. Spatial or network autocorrelation can violate the assumption that flows are independent and not associated with or influenced by other flows [8-9]. Eigenvector spatial filtering has been proposed as a way of accounting for this when modelling spatial interaction flows using the *T* statistic [8-10]. For the analysis, the *T* statistic is implemented using a binary contiguity matrix based on the criterion of contiguity.

4. Analysis

Three spatial interaction models were estimated in R Studio. Bicycle trip counts were the dependent variable, the zonal attributes were independent explanatory variables, and the distance or time of approximated cycle routes as a measure of spatial separation. Akaike's information criterion (AIC) was used to compare the estimated models. The residual likelihood was calculated as a final measure of comparison. Model #3 which included variables zonal attributes at the origin and destination, topography, and quietest distance as the measure of separation produced the best model. There was no network autocorrelation present.

Figure 2. Model #3 with quietest distance route.

```
summary(model3)

Model:

Call:
z5$zelig(formula = Trips ~ Population.o + Points_of_Interest.o +
    BusStops.o + Institutions.o + Commercial.o + Residential.o +
    Population.d + Full_time_jobs.d + Part_time_jobs.d + Points_of_Interest.d +
    BusStops.d + Institutions.d + Commercial.d + Residential.d +
    Topography + quietest_distance, data = OD_table.sf)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-15.661   -1.467   -0.527   -0.240   32.685

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                  2.000e+00  4.037e-02  49.544  < 2e-16
Population.o                -4.379e-05  9.858e-06  -4.442  8.9e-06
Points_of_Interest.o        -7.885e-04  4.939e-05 -15.964  < 2e-16
BusStops.o                   1.713e-02  9.561e-04  17.919  < 2e-16
Institutions.o               1.472e-02  7.938e-04  18.545  < 2e-16
Commercial.o                -3.171e-03  3.999e-04  -7.929  2.2e-15
Residential.o               -7.324e-05  2.950e-05  -2.482    0.013
Population.d                -9.174e-05  1.075e-05  -8.538  < 2e-16
Full_time_jobs.d             1.187e-04  9.274e-06  12.802  < 2e-16
Part_time_jobs.d             4.152e-04  2.002e-05  20.742  < 2e-16
Points_of_Interest.d         7.038e-05  5.144e-05   1.368    0.171
BusStops.d                  -1.292e-02  1.245e-03 -10.383  < 2e-16
Institutions.d               2.324e-02  8.559e-04  27.157  < 2e-16
Commercial.d                -5.888e-03  4.131e-04 -14.253  < 2e-16
Residential.d                5.879e-04  3.363e-05  17.481  < 2e-16
Topographylower city - rural -2.427e+00  6.227e-02 -38.972  < 2e-16
Topographyrural             -5.344e-01  3.776e-02 -14.155  < 2e-16
quietest_distance           -3.405e-04  3.815e-06 -89.259  < 2e-16

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 94387  on 9800  degrees of freedom
Residual deviance: 61717  on 9783  degrees of freedom
AIC: 63172
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Figure 3. Model #3 had the lowest AIC value among all three models that were estimated.

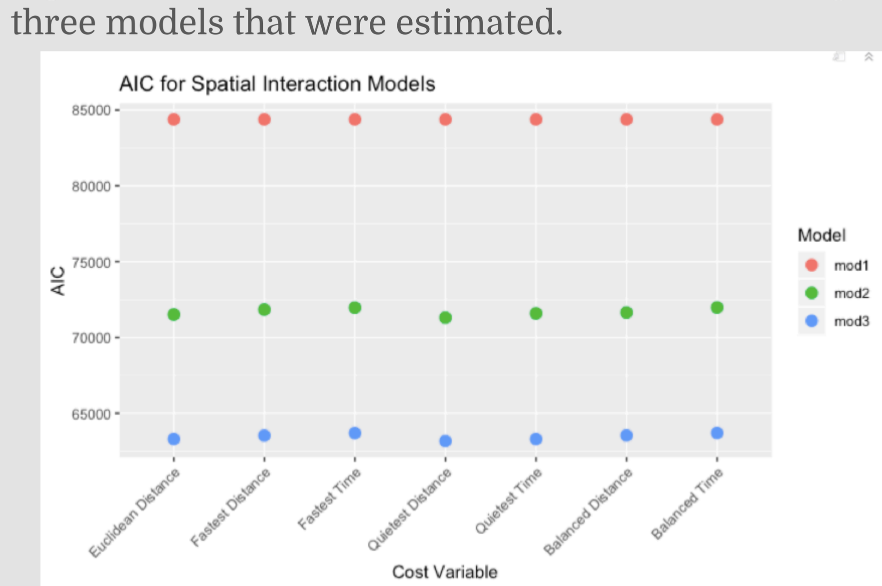
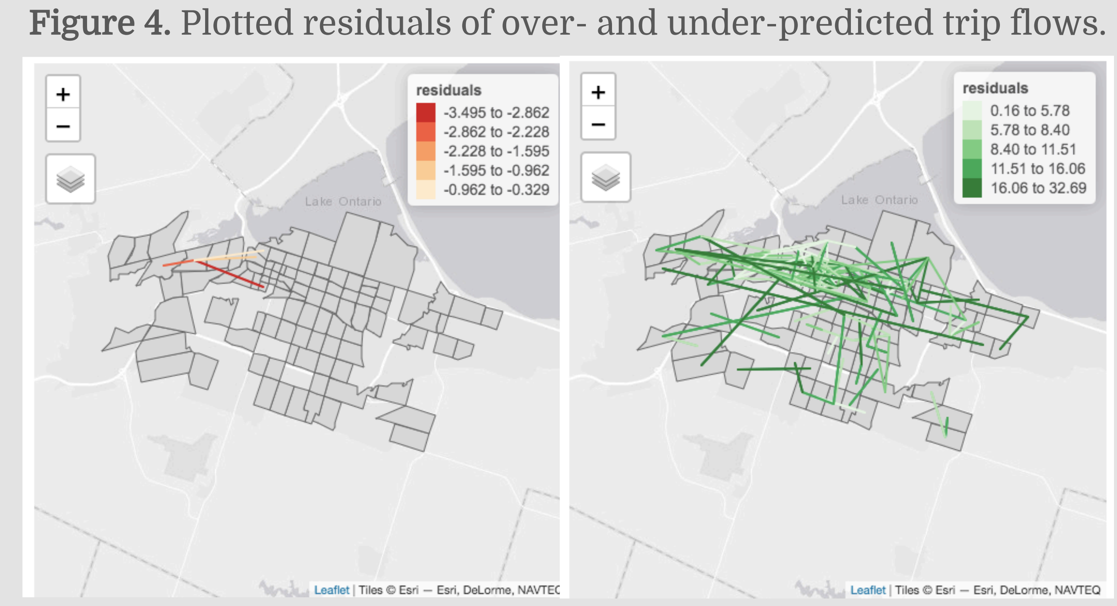


Figure 4. Plotted residuals of over- and under-predicted trip flows.



5. Discussion

The best model reveals that quiet routes that allow bicyclists to avoid traffic while minimizing distance best explain the pattern of travel by bicycle in Hamilton. This indicates that people who travel by bicycle in Hamilton are likely to be seeking out routes that are less busy and potentially more enjoyable. This finding is consistent with a recent study that used GPS data to investigate bicycle route preferences [11]. While we cannot know with complete certainty which routes were travelled, by exploring different types of routes in our models we were able to provide statistical support for quiet routes that minimize distance.

Furthermore, the model reveals that points of interest at the zone of origin have a negative influence on the number of expected bicycle trips. This can create more intervening opportunities that ultimately reduce the need to travel. The model also uncovered a positive relationship between diversity of land use, characterized by mix of uses at the destination, and the expected number of trips - which is also consistent with other studies [5]. Topography was found to have a negative relationship with the expected number of bicycle trips, likely because it increases effort to travel.

6. Future Research

The analysis of flows that were over- and under-predicted (Figure 4) presents opportunity to explore the built environment along approximated bicycling routes. We hypothesize that shortest-path quiet routes may have attributes that promote or hinder travel by bicycle, including bicycle facilities or lower speed limits, which leads to more bicycling than expected from the model. There are many street audit tools available to systematically assess bikeability. This is the topic of ongoing research as part of this thesis project. Bikeability audits will be conducted along quietest routes for 12 O-D pairs that were under-predicted.

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