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TRANSPORT FINDINGS

Measuring the Added Effectiveness of Using Detailed Spatial and Temporal Data in Generating Accessibility Measures

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Transport Findings

It is hypothesized that spatially disaggregated and temporally variable data will lead to more accurate determinations of accessibility. This paper examines whether such measures are more effective in predicting public transport mode share and commute duration in Montreal, Canada through regression models. While results show that the model fit to predict mode share is better when accessibility is generated using detailed spatial and temporal data, the improvement is minimal. In predicting commute duration, no improvements are observed. Furthermore, the change in resulting values of accessibility between measures is observable and varies depending on the configuration and frequency of transport supply.

RESEARCH QUESTION AND HYPOTHESES

A current trend among researchers is the pursuit of more complex approaches to measure accessibility (Geurs, Krizek, and Reggiani 2012), some focusing on time-sensitive components, i.e., variations in transit service (Boisjoly and El-Geneidy 2016; Conway, Byrd, and van der Linden 2017; Farber and Fu 2017; Stepniak et al. 2019), while others aim to minimize errors that arise due to spatial aggregation (Apparicio et al. 2017; Hewko, Smoyer-Tomic, and Hodgson 2002). However, the effectiveness of these resource-heavy approaches remains to be reviewed.

Our research examines differences between three accessibility measures, two generated using the Conveyal Analysis tool (Github 2018); both of which use fine-grained spatial units of analysis, but one uses a static departure time while the other derives median travel time based on variable departures. The third is the conventional approach evaluated at census tract (CT) level and uses a static departure time. The impacts of the three accessibility measures are compared in a series of mode share as well as commute duration regression models.

METHODS AND DATA

The three accessibility measures are referred to as (a) *Conventional*; (b) *Detailed 8 a.m.*; and (c) *Detailed 7–9 a.m.* and are cumulative-opportunity measures. Data inputs include number of jobs available at CT level as well as the General

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Transit Feed Specification (GTFS) and street network files that are used to generate travel times between origins and destinations for the specified spatial and temporal unit of analysis.

Job data is obtained from Statistics Canada 2016 Census Flow tables for the Montreal metropolitan region that represent the number of commuters, by mode of transport, commuting between pairs of CTs. Here, we consider that the sum of all jobs available at different times throughout the entire day is assumed to be available at all times. The number of jobs available in a CT is the sum of all arriving commuters and is either summarized spatially at the CT centroid in the *Conventional* measure or divided according to areal proportion among grid cells intersecting a given CT.

For the *Conventional* measure, a public transport travel time matrix (done using the Add GTFS to a Network Dataset toolbox for ArcMap) is generated with scheduled GTFS data for an 8 a.m. departure on May 16, 2017. Travel time matrices for *Detailed* measures are generated using Conveyal Analysis. For the *Detailed 8 a.m.* measure, median travel time is taken using GTFS data, based on departure times from 8:00 to 8:01 (approximately 8 a.m.) and for the *Detailed 7–9 a.m.* measure, median travel time is based on departure times at one-minute intervals between 7 and 9 a.m. Travel time threshold used in all measures is 50 minutes, the median travel time for all commuters in the Montreal region.

To generate the spatial level of analysis used in the *Conventional* measure, the CT and travel time between CT centroids is used to determine the number of reachable jobs. For the *Detailed* measures, travel time is calculated between the centroids of square raster cells (each approximately 0.05 km^2) of a regular grid covering the study area. Then the accessibility values from the *Detailed* measures are aggregated to CT level (unweighted by population) to compare with the *Conventional* measure with zero-accessibility grid cells removed prior to aggregation. Despite this, the prevalence of very low accessibility values in outer regions could have resulted in some aggregation error in this process. A person-weighted average would be an improvement on the methodology but the population data was not available at the grid cell level.

Linear regression models were developed for percentage of commuters using public transport leaving the origin CT (assumed to be constant). Note here that there are two accessibility variables, a squared and a linear term, that enter into the models and reflect the quadratic relationship that we have described in previous research between public transport mode share and accessibility (Cui and El-Geneidy 2019). Multilevel mixed effects models developed previously by Cui et al. (2019) have been used here to model commute duration. Accessibility measures to jobs and workers at both the origin and destination CTs are generated, which accounts for the impact of competition, and are entered into the models as per the previous setup used by Cui et al. (2019) and Levinson (1998).

FINDINGS

The percent difference in accessibility at CT level between *Detailed* and *Conventional* measures are shown in Figure 1. We observe that differences between *Detailed* and *Conventional* measures are minimal with some decreases in the accessibility values generated using the *Detailed* measures compared to the *Conventional* measure in the central area and more significant changes at the tips of the Island of Montreal. In general, there are more instances of decreases than increases observed for areas off the island, which may be explained by the use of aggregated average accessibility, which is sensitive to very low values, resulting in lower accessibility values using *Detailed* measures. In addition, significant increases are observed in some suburban CTs served directly by commuter trains.

In Figure 2, areas of increases and decreases are observed across the region, which could be related to the frequency and timing of transit service in these areas. For example, when departure times align with transit service at 8 a.m. (i.e., commuters arrive just in time for the service at 8 a.m.), use of variable departure times would not improve accessibility especially if service is infrequent and long wait times are observed. Similarly, the radial pattern of the change in accessibility (i.e., the percentage of increase in accessibility is highest at the center and then decreases in places further away, after which the increase becomes a decrease even further from the center), is also emphasized by infrequent service, where areas at certain distances from stations are penalized when variable departure times are considered due to lack of coordination between access times and scheduled service.

Results of regression models for mode share and commute duration are shown in Tables 1 and 2, respectively. The R^2 value of the mode share models is highest using the *Detailed 7–9 a.m.* measure but relative improvement is minimal at 1.3%. Also, we observe in Table 1 that coefficients of accessibility variables increase in magnitude as more-detailed data is used in accessibility measures, similar to results from Owen and Levinson (2015) . It seems that more-detailed measures are more effective in capturing the impacts of accessibility on mode share. For commute duration, *Detailed* measures did not improve model fit and accessibility to jobs at the origin variable is not significant when these measures are used. One limitation of the study is that spatial autocorrelation was not addressed for the mode share models whereas use of the multilevel models for commute time account, to some extent, for this factor.

Our analysis demonstrates that the use of detailed data to generate accessibility measures may improve model fit in certain analyses. In addition, the study shows that there exist substantial differences in accessibility values generated using *Detailed* measures and *Conventional* measures, particularly in areas with infrequent service.

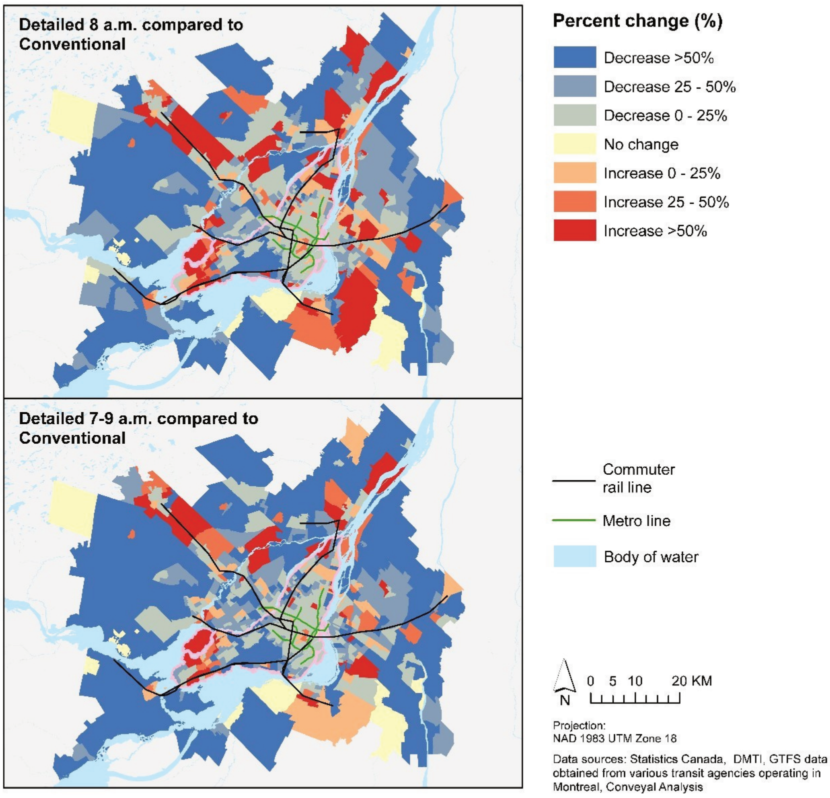

Figure 1: Comparison of the Percent Change of Accessibility Aggregated at the CT Level Between the *Detailed* Measures and the *Conventional* Measure

Note that the reference for determining percent difference is the second measure mentioned.

ACKNOWLEDGMENTS

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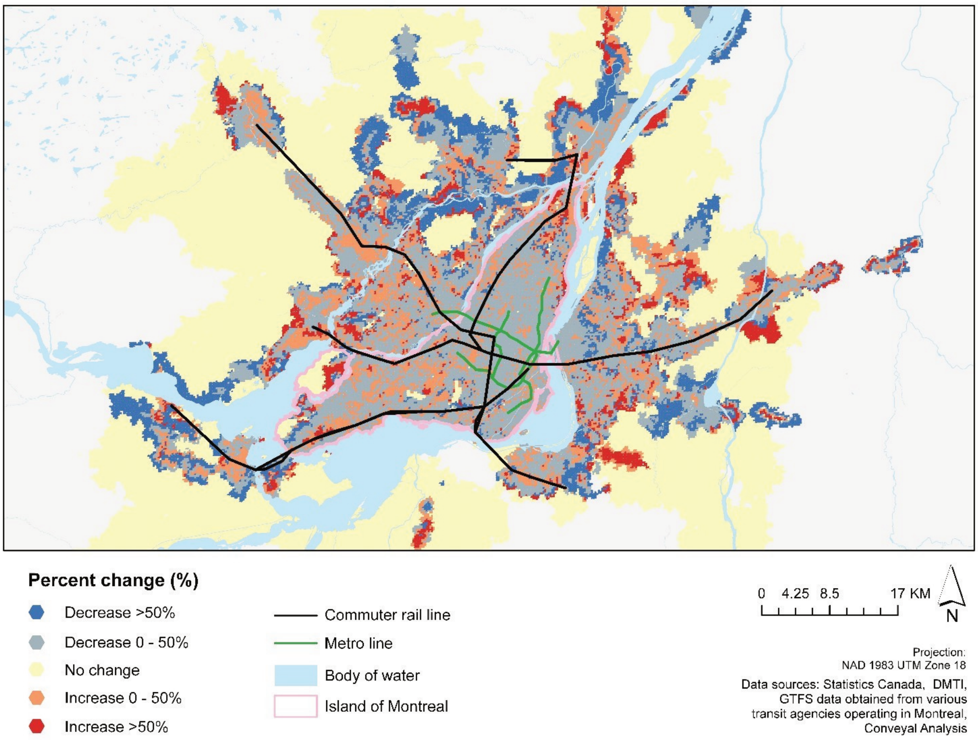

Figure 2: Comparison of the Percent Change of Accessibility at Grid Cell Centroids Between *Detailed* Measures (7–9 a.m. Compared to 8 a.m.)

Table 1: Results of the Regression Models for Public Transport Mode Share for Each Measure

	Conventional		Detailed 8 a.m.		Detailed 7-9 a.m.	
	Coefficient	Signif.	Coefficient	Signif.	Coefficient	Signif.
Accessibility Measures						
Accessibility to jobs (%)	0.639	***	0.862	***	0.917	***
Accessibility to jobs squared (%^{2})[a]	−0.005	***	−0.009	***	−0.010	***
Control Variables						
Population density (thousand persons/km^2)	0.405	***	0.364	***	0.336	***
Average age	−0.206	***	−0.184	***	−0.162	***
Average number of people in a household	−0.356		0.050		0.427	
Social deprivation indicator (decile)	1.115	***	1.111	***	1.187	***
Network distance to closest rapid transit station (km)	−0.354	***	−0.329	***	−0.339	***
Network distance to closest highway on-ramp (km)	0.120		0.088		0.101	
Constant	18.634	***	16.451	***	14.726	***
Akaike's information criterion | Bayesian information criterion	6475 | 6514		6434 | 6478		6432 | 6476	
R^2	0.785		0.794		0.795	

*p<0.05 ** p<0.01 *** p<0.001

[a]Cui and El-Geneidy (2019) found a nonlinear relationship between accessibility and mode share that is approximated using a squared accessibility term here: a negative squared accessibility term and a positive linear term implies a relationship characterized by a concave parabola where increasing accessibility leads to increase in mode share up until the vertex, where increasing accessibility has a negative impact on mode share.

Table 2: Results of the Multilevel Regression Models for Public Transport Commute Duration for Each Measure

	Conventional		Detailed 8 a.m.		Detailed 7-9 a.m.	
	Coefficient	Signif.	Coefficient	Signif.	Coefficient	Signif.
Accessibility Measures						
Accessibility to jobs at origin (%) [a]	−0.005	***	−0.001		−0.002	
Accessibility to workers at origin (%) [a]	−0.005	**	−0.009	***	−0.009	***
Accessibility to jobs at destination (%) [a]	0.003	***	0.005	***	0.006	***
Accessibility to workers at destination (%) [a]	−0.004	***	−0.006	***	−0.007	***
Control Variables						
Median household income (thousand CAD$)	0.001		0.001		0.001	
Average age	−0.006	***	−0.006	***	−0.007	***
Average number of people in a household	−0.009		−0.009		−0.010	
Unemployment rate (%)	0.002		0.002		0.002	
People spending >30% of income on housing (%)	−0.003	***	−0.003	**	−0.003	**
Immigrants (%)	0.005	**	0.005	*	0.005	*
People with high school degree as highest level of education (%)	−0.0004		−0.0004		0.000	
Network distance to closest heavy rail transit station (km)	0.027	***	0.027	***	0.027	***
Network distance to closest highway on-ramp (km)	0.015	***	0.015	***	0.015	***
Network distance to city center (km)	0.018	***	0.018	***	0.018	***
Constant	3.863	***	3.853	***	3.865	***
Akaike's information criterion | Bayesian information criterion	477208 | 477390		476914 | 477097		476705 | 476887	
Snijders/Bosker R^2 Level 1	0.4927		0.4921		0.4922	
Snijders/Bosker R^2 Level 2	0.8717		0.8698		0.8695	

*p<0.05 ** p<0.01 *** p<0.001

[a]Four accessibility measures enter into the models and the impact of the coefficients are as expected with the exception of the accessibility to workers at the origin variable where one would expect that increased accessibility to workers at home would increase travel time as a sign of increased competition. At the same time, increased accessibility to jobs at destination increases travel time, which is expected.

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