Titre: Title:	Developing a web-based accessibility calculator prototype for the Greater Montreal Area
Auteurs: Authors:	Antonio Páez, Md Moniruzzaman, Pierre-Léo Bourbonnais, & Catherine Morency
Date:	2013
Type:	Article de revue / Article
Référence: Citation:	Páez, A., Moniruzzaman, M., Bourbonnais, P.-L., & Morency, C. (2013). Developing a web-based accessibility calculator prototype for the Greater Montreal Area. Transportation Research Part A: Policy and Practice, 58, 103-115. https://doi.org/10.1016/j.tra.2013.10.020

Transportation Research Part A 58 (2013) 103–115

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Developing a web-based accessibility calculator prototype for the Greater Montreal Area

Antonio Páez [a,*], Md. Moniruzzaman [a,1], Pierre-Leo Bourbonnais [b,2], Catherine Morency [b,2]

[a] Centre for Spatial Analysis, School of Geography and Earth Sciences, McMaster University, 1280 Main Street, Hamilton, Ontario L8S 4K1, Canada

[b] ÉcolePolytechnique, département des génies civil, géologique et des mines, P.O. Box 6079, Station Centre-Ville, Montréal, Québec H3C 3A7, Canada

ARTICLE INFO

Article history:
Received 7 October 2011
Received in revised form 12 October 2013
Accepted 14 October 2013

Keywords:
Accessibility
Travel behavior
Active travel
Internet mapping
Greater Montreal Area

ABSTRACT

A mixture of modes is considered a key element towards sustainable transportation. New technologies that provide information about various modes and environments can help to inform choices regarding travel and accessibility. In this paper we describe the development of a web-based accessibility calculator prototype for the Greater Montreal Area in Canada. The core of this tool is a statistical model of trip length developed using the spatial expansion method. The model is used to obtain estimates of trip length for a desired profile, based on attributes such as age, gender, family structure, and mode of travel, as well as geographical location. These estimates are used to calculate a cumulative opportunities accessibility measure to different types of essential destinations. Travel behavior information is drawn from Montreal's 2008 Household Travel Surveys. Geocoded information about trip origins and destinations is used to calculate trip length. A broad array of covariates related to individual and household attributes, and urban form are used. A geocoded business point database is used for the calculation of cumulative opportunities. To simplify the use of the accessibility calculator, the model is implemented in a user-friendly way using Google Maps API v3 and a convenient interface. Different possible uses of the accessibility calculator are illustrated in the paper. The accessibility calculator can be used by members of the public or planners/policy makers to measure the level of accessibility for a specific address and personal profile by various modes of transportation.

1. Introduction

The sophistication of tools to conduct inexpensive searches using information and communications technologies (ICT) has grown by leaps and bounds over the past two decades. The emergence of the World Wide Web, and the amount of information that can now be retrieved, greatly facilitate doing specialized searches. Tools such as Google, Yahoo, and Bing Maps have popularized geomatics technology, and made it accessible to greater segments of the public.

To be sure, the impact of ICT on travel behavior has long been a topic of interest from a transportation perspective (e.g. Mokhtarian et al., 2006; Wang and Law, 2007). However, the impact of telework, an early focus of this literature (Mokhtarian, 1988, 1991), is now eclipsed by the way individuals interact with technology in preparation for, during, and after travel. Search engines routinely include travel information by different modes. Local transit operator offer online route planners with schedules, so that users can consult the time of the next bus to their destination, the number of connections involved,

* Corresponding author. Tel.: +1 (905) 525 9140x26099; fax: +1 (905) 546 0463.
E-mail address: paezha@mcmaster.ca (A. Páez).
[1] Tel.: +1 (905) 525 9140x26099; fax: +1 (905) 546 0463.
[2] Tel.: +1 (514) 340 4711x4502; fax: +1 (514) 340 4173.

0965-8564
http://dx.doi.org/10.1016/j.tra.2013.10.020

and the fare as well. No longer tied to bulky computing equipment, simple possession of a mobile device is sufficient to replace a navigator to offer detailed instructions about routes.

Of particular interest from this perspective are tools that offer information about travel by different modes. Some efforts have begun as academic projects, such as the cycling route planner developed by Su et al. (2010). Many others have been commercial in nature, including WalkScore[3] and Google Transit[4]. In this paper, we present an alternative approach to finding information about travel and accessibility.

Perhaps the most direct indicator of walkability (or drivability, cyclability, etc.) is the actual way people travel. Now, it would be very difficult for an individual person to collect information on the mobility patterns of others. Fortuitously, many urban areas deploy travel surveys to collect statistically representative samples that essentially amount to the same thing: asking a large number of people about their travel patterns. Based on information obtained from one such large travel survey, in this paper we describe the development of a prototype accessibility calculator for the Greater Montreal Area, in Canada. The core of the calculator is a cumulative opportunity measure that counts the number of opportunities of a certain type that can be reached given a trip length by a certain mode. An innovative aspect of the calculator is that the trip lengths can be customized for specific individual profiles and locations, in the manner of the relative accessibility indicators introduced by Páez et al. (2010b).

The tool can be used in multiple ways. For members of the public, the accessibility calculator provides a convenient way to explore the mobility and accessibility patterns in a region. The calculator can be seen as a substitute to directly querying an individual, with a certain profile, and living in a certain location, about her trips and level of accessibility (i.e. the number of amenities that can be reached) when using a given mode for transportation. Since the values are estimated based on a statistical model, the accessibility calculator may not provide exact levels of accessibility for any one actual individual. However, they represent our best guess (validated statistically) about typical behavior in the population. The accessibility calculator can also be used by planners and/or policy makers, to assess the range of potential impacts of an intervention, on individuals with various characteristics. Real estate agents and/or developers may use this tool to help their clients find better matches of locations to lifestyles. In order to simplify the calculation of accessibility for use by the general public and other interested parties, the tool is implemented in the form of a web-based calculator, using Google Maps API v3 and a convenient interface.

In the following sections we discuss the background and conceptual approach adopted for this tool, as well as the technical and technology aspects of developing the web-based accessibility calculator prototype. Suggested uses include measuring the level of accessibility for a specific address, which, given a specific personal profile, can be compared to different addresses; to identify and explore local activity opportunities reachable by walking for a specific personal profile; to compare accessibility by different modes of transportation; to assess the potential of a residential location to support walking as a mode of travel; or to evaluate likely changes in accessibility throughout the lifespan of a resident. Some of these uses are illustrated in the paper.

2. Background

2.1. Factors influencing travel behavior

It is well known that travel behavior is influenced by a number of factors, typically classified as individual (socio-economic and demographic), those related to the attributes of the mode of travel and the routes available, and the physical environment that provides the context for movement. In this way, we know that travel behavior changes throughout the life course, with mobility reaching a peak for mature adults but being more limited for younger and older people (Buliung et al., 2012; Schwanen and Páez, 2010). There is also ample evidence that men and women display differences in their patterns of mobility and accessibility, with females generally being less mobile (Dobbs, 2005; Kwan, 1999; McLafferty and Preston, 1997; Turner and Niemeier, 1997). Related to this, household type can also influence mobility and accessibility, as household members share or impose mobility responsibilities with or on one another (Gliebe and Koppelman, 2002; Scott and Kanaroglou, 2002). Employment status, by imposing fixed spatial and temporal anchors, and income, by constraining or enhancing the means for travel, are also known to influence travel behavior (Mokhtarian and Chen, 2004).

More recently, in addition, there has been much interest in the impact of the built environment and urban form on travel behavior (Cervero, 2002b). Configuration of our urban landscapes, both in terms of land uses and design factors, has been shown to influence mode choice (Cervero, 2002a; Rodriguez and Joo, 2004) and vehicle holdings and use (Bhat et al., 2009). By mediating the use of different modes of transportation, the built environment has also been linked to issues in public health. Sedentary lifestyles encouraged by auto-oriented development have become a major international public health concern (Sallis et al., 2009). On the other hand, there is well-established evidence indicating that pedestrian friendly neighborhoods are more conducive to active travel, and thus increased physical activity (Frank et al., 2003, 2004; Sallis et al., 1998).

Various measures have been proposed that aim to capture the character of the built environment, and particularly its density, diversity, and design (Cervero and Kockelman, 1997). These include the index developed by Frank et al. (2010) based

[3] WalkScore®: http://www.walkscore.com/.

[4] www.google.com/transit.

on the z-score of four items: intersection density, residential density, retail floor area ratio, and land use mix, all measured within a 1 km network-based buffer or the census block of an address. The first item is an indicator of a design feature of the environment. Land use density measures the proximity of opportunities. In particular, large values of the retail floor area ratio may be indicative of development that favors the use of motorized modes, or that presents a barrier to people on foot (Moudon et al., 2006). Lastly, land use mix has been found to increase the ease with which various modes can be used (Cervero, 1988). An alternative approach, developed by Kuzmyak et al. (2005), is to calculate a walk opportunities index. This index simultaneously takes into account the number, character, and desirability of key activities located within walking distance of a household, set to 0.4 km. The walking opportunities index is a gravity-type (i.e. weighted) accessibility indicator, with the weights given in terms of size and attractiveness of the opportunities, and geographical distance.

Recent research also finds that micro-scale attributes of the physical environment particularly affect the use of slow modes (Ewing and Handy, 2009; Moniruzzaman and Paez, 2012). Alas, these attributes are seldom collected in a systematic way (Parmenter et al., 2008), and will not be considered further.

2.2. Information and travel behavior

In addition to the factors discussed above, routine travel of people to various activity nodes is influenced by their awareness of their surroundings (Brantingham and Brantingham, 2008). It is thus possible that increasing the geographical awareness of travelers can encourage healthy and sustainable transportation and residential choices. Indeed, the experimental evidence available suggests that access to information can influence choices in a positive way, for instance by allowing users to choose residential locations that support multi-modal travel (Rodriguez et al., 2011).

The basic intuition that transport information can shape mobility patterns (q.v. Byrne, 2011) is in all likelihood behind the growing popularity of information technologies regarding various modes of transportation, routes available, and the characteristics of local environments. Early information tools include in-vehicle navigation systems, initially developed and commercialized in the 1970s and 1980s (French, 2006). These systems fully came of age with the widespread availability of Global Positioning Systems, and are becoming a standard feature of new vehicles (Skog and Handel, 2009). The commercial success of these in-vehicle navigation technologies was supported largely by a market mostly set on private motorization. As the technology has become more widely adopted, new uses continue to be found that support accident detection, traffic control, and other applications (Skog and Handel, 2009).

More recently, other technologies have emerged that make it easier to provide information regarding alternative modes of transportation – not only the car – to large segments of the public. Advances in geospatial technology, in particular web-based mapping, makes it possible to distribute information massively to users of urban spaces at a relatively low cost. Applications that benefit from internet technologies have burgeoned, including applications that allow a traveler to identify routes, such as Yahoo Maps, Bing Maps, and Google Maps. Travel and route planners are now offered by transit agencies around the world, as well as Google Transit (Cherry et al., 2006; Currie and Gook, 2009; Watkins et al., 2010). Other efforts have aimed at providing information for specific modes, such as planners for cycling (Su et al., 2010). WalkScore, another specialized index, reports a summary measure of how supportive a certain location is for a specific mode of transportation (e.g. walking). WalkScore employs the Google Local Search API to retrieve information about local amenities within a given distance of the location (i.e. 0.4 km). Instances of ten to fifteen amenity categories (e.g. groceries, restaurants, schools, parks, libraries, banking, post office, fitness, hospitals, and day-care) are passed onto a scoring algorithm that assigns points based on the distance to the amenities, and that reports a standardized sum to give a score for the entered address ranging between 0 (for low walkability) and 100 (for high walkability).

There are several reasons why offering information about a more complete menu of transportation options is a matter of growing importance. Car-driven congestion continues to be a blight on many metropolitan regions, and the high cost that it imposes creates important policy concerns (Glaeser, 2012; Urban Transportation Task Force, 2012). Preliminary evidence indicating that car travel has peaked or even declined in several countries (Kuhnimhof et al., 2012a, 2012b; Metz, 2012) may portend changes in travel modality and an increase in the use of alternative modes. Also, importantly, there is an increased awareness of the potentially negative health effects of our continued reliance on cars (Frank et al., 2004), and the potential benefits of shifting to transit and active modes (Lachapelle et al., 2011; Newman and Matan, 2012; Rabl and de Nazelle, 2012).

In a recent review of transport information and travel behavior, Byrne (2011) suggests that a focus on the user will be important to ensure the success of future transportation information strategies. Our approach, therefore, is to develop indicators of accessibility that are responsive to variations in user's attributes, based on previous research showing significant geographical differences in travel behavior (Morency et al., 2011; Roorda et al., 2010). Consequently, in order to assess opportunities for activity participation, we will implement our accessibility indicators while taking into consideration actual measures of travel behavior, as suggested by Páez et al. (2010b). This is discussed in more detail next.

2.3. Measuring accessibility

Accessibility is conventionally defined as the potential for reaching opportunities. A commonly used measure of accessibility is a member of the gravity family of indicators, namely the cumulative opportunities indicator. Given a set of $j = 1, \ldots, n$ opportunities of type k, this indicator is typically defined as follows:

$$CO_i^k(\delta) = \sum_{j=1}^{n} I(d_{ij}^k \leq \delta) \tag{1}$$

where $I(\bullet)$ is an indicator function that takes the value of 1 if the argument is true and zero otherwise, d_{ij} is the distance between location i and opportunity j, and δ is a distance threshold. An unweighted indicator (i.e. cumulative opportunities) offers an intuitively appealing interpretation, as it is simply the number of opportunities available within distance δ of location i. Seen as a kernel estimator, an unweighted indicator tends to introduce less smoothing to the opportunity surface (O'Kelly and Horner, 2003). As is the case for other accessibility indicators, implementation typically is done by selecting a reasonable or desired threshold δ, for instance 0.4 or 1 km. *A priori* selection of the threshold, however, ignores the fact that people may be willing and/or able to travel longer or shorter distances in the course of their daily activities (Paez et al., 2012). The indicator can be modified to introduce a greater degree of sensitivity, by introducing an adaptive threshold that is a function of the personal profile of the traveler and the geographical location. This gives a relative accessibility indicator as follows (Páez et al., 2010b):

$$R_{pi}^k(\delta_{pi}) = \sum_{j=1}^{n} I(d_{ij}^k \leq \delta_{pi}) \tag{2}$$

As seen in Eq. (2), the threshold is now indexed by personal profile p and location i, and therefore is responsive to socioeconomic and demographic attributes (e.g. seniors tend to be less mobile: see Mercado and Páez, 2009; Schmocker et al., 2005), as well as location (e.g. suburban residents in general tend to display greater mobility levels: see Morency et al., 2011). Use of an adaptive threshold makes it possible to assess the relative differences in accessibility levels accrued by identical personal profiles at different locations, or different profiles at the same location.

In order to implement the relative accessibility indicator, a rule or set of rules must be selected for the adaptive threshold, preferably based on actual mobility measures. There are a number of measures of mobility that could potentially be adopted, including average trip length (Morency et al., 2011), maximum distance traveled during a day (Casas, 2007), or the use of estimates obtained from a spatial interaction model (Clarke et al., 2002; Scott and Horner, 2008). In the implementation below, we used trip length as an indicator of the revealed preferences of individuals to travel longer or shorter distances, and specifically, model-based estimates of trip length derived based on the application of a spatially-varying coefficients model calibrated according to the spatial expansion method (Casetti, 1972). This approach has been used to calculate a cumulative opportunities to different types of opportunities such as health care facilities (Páez et al., 2010a), food outlets (Páez et al., 2010b), contact with various population types (Farber et al., 2011), children day-care locales (Paez et al., 2012), and jobs by single parents (Paez et al., 2013). The data and methods used to implement the indicators of relative accessibility are described next.

3. Data

Two datasets were used to implement the relative accessibility indicator for the Greater Montreal Area, namely Montreal's travel survey and a geocoded business location file for the region. Both datasets correspond to 2008.

3.1. Montreal's travel survey

Montreal's travel survey (http://www.cimtu.qc.ca/EnqOD/Index.asp) is the major survey of its type in Quebec, Canada. This extensive cross-sectional origin–destination (OD) travel survey program has been carried out approximately every five years since 1970, with the objective of providing information to support planning, operations, and research. The coverage of the survey as of 2008 comprises the entire metropolitan area as defined by the Census, including the cities of Montreal, Laval, and Longuecil via the North and South Shores. Each cross-section of the survey collects information concerning approximately 5% of all households living within the jurisdiction of the survey area. In 2008, the survey was completed by 66,100 households (about 4.1% of total households) which comprised a population of about 156,700.

The main information collected relates to all trips made during the day previous to the survey by members of participating households. As a standard procedure, participants are selected randomly for the survey, and then validated for representativeness. In addition to travel information, different attributes of the household and its members are asked, including the age of household members, their gender, and driver licence and vehicle ownership. The origin and destination of each trip is geocoded with x–y coordinates using structure databases on addresses, nearest intersections, and trip generators. High quality geocoding makes it possible to implement extensive spatial analysis of individual's travel behavior.

For the purposes of this research, we have extracted all home-based trips from the database, to obtain a subset of 283,615 trips made by 56,668 individuals. Use of home-based trips means that the indicator implemented is accessibility at the place of residence. A different implementation could be of accessibility from the perspective of place of employment, although we do not pursue such route further in this paper.

3.2. Business location file

The cumulative opportunities indicator counts the number of opportunities available within a given threshold distance. The set of opportunities for our implementation is extracted from a geocoded business point dataset. The dataset provides an exhaustive collection of business locales tagged with their respective Standard Industrial Classification code. The 4-digit Standard Industrial Classification code allows us to extract specific business types from the much larger dataset. For our study, we have extracted a subset of business types representing destinations routinely accessed by the public, including banking, dining, grocery, entertainment, shopping, and educational opportunities, as well as pharmacies, libraries, fitness clubs, and health care facilities. This range of opportunity types was selected for illustrative purposes, and can be expanded and/or modified as desired.

4. Methods

4.1. Spatial expansion method

In order to obtain person- and location-specific estimates of trip length for the adaptive threshold in Eq. (2), we estimated a regression model with spatially expanded coefficients. The expansion method, introduced by Casetti (1972) to the geographical analysis literature, essentially codifies a modeling philosophy that assumes the existence of substantive knowledge (in a regression model the independent variables) and acknowledges the possible presence of contextual variations (if spatial, introduced by means of the geographical coordinates of the observations). Technically, the method operates by expanding some or all of the coefficients in a regression model as a function of the coordinates, say u_i and v_i, of observation i. Consider the following model with substantive variables X and Z, (some) spatially-fixed coefficients β, and (some) spatially-varying coefficients θ (the term ε is the usual regression residual):

$$Y_i = \sum_j X_{ij}\beta_j + \sum_s Z_{is}\theta_s(u_i, v_i) + \varepsilon_i \tag{3}$$

The spatially-varying coefficients are a function of the coordinates u and v. Implementation of the expansion method is achieved quite simply by introducing interactions between the set of substantive variables Z and a trend surface of an appropriate order (e.g. linear, quadratic, etc.) A linear expansion for a given coefficient θ_s would be obtained as follows:

$$\theta_s = \theta_{s1} + u_i\theta_{s2} + v_i\theta_{s3} \tag{4}$$

whereas a quadratic expansion would be:

$$\theta_s = \theta_{s1} + u_i^2\theta_{s2} + u_i\theta_{s3} + u_i v_i\theta_{s4} + v_i\theta_{s5} + v_i^2\theta_{s6} \tag{5}$$

It is straightforward to see that a spatially-varying coefficient is composed of a sequence of coefficients associated with interaction terms between the corresponding substantive variable Z_s and the elements of the trend surface. In the case of the linear trend, this is:

$$Z_{is}\theta_s(u_i, v_i) = Z_{is}(\theta_{s1} + u_i\theta_{s2} + v_i\theta_{s3}) = Z_{is}\theta_{s1} + Z_{is}u_i\theta_{s2} + Z_{is}v_i\theta_{s3} \tag{6}$$

The term $Z_{is}\theta_{s1}$ is the system-wide (mean) effect. As the model is evaluated at different sites (by changing the coordinates u and v), the effect is to introduce variations in the value of the spatially-varying coefficient, i.e., by adding $Z_{is}u_i\theta_{s2}$ and $Z_{is}v_i\theta_{s3}$ to the system-wide effect as indicated. The overall coefficient is thus specific to a location, and the response (the estimated value of Y) is influenced as well by the level of Z_s. In this way, person- and location-specific estimates of Y can be obtained once the coefficients have been estimated. The model can be estimated under suitable assumptions using ordinary least squares, and the significance of the coefficients (fixed and varying) and goodness of fit of the model are assessed as usual.

4.2. Selection of variables and estimation results

The dependent variable in the analysis is the straight line distance (in km) from the origin to the destination for each home-based trip in the database. A more sophisticated variable would be network distance, but implementation of this variable involves the calculation of network buffers, which poses considerable challenges with respect to the use of web-based geocomputation. Fortunately, straight line distance and network distance are highly correlated in the case of Montreal (Apparicio et al., 2008). The coordinates used for the expansion of the spatially-varying coefficients therefore correspond to the place of residence of the respondents. Latitude and longitude coordinates were transformed to make the usually large numbers commensurate with the magnitude of other variables, and so avoid poorly scaled matrices in the estimation of the coefficients. The distribution of the distance variable, as usual, is strictly positive and displays a long right tail. The variable is transformed using the natural logarithm to reduce the scale and in order to ensure that estimated values of trip length are positive.

Independent variables were selected to cover a broad range of socio-economic and demographic attributes that affect travel behavior. Many of these variables have been found in previous research to influence trip length. For instance, age has been found to have a negative association with distance traveled (Mercado and Páez, 2009; Morency et al., 2011; Schmocker et al., 2005). Females tend to travel shorter distances (Kwan, 1999; McLafferty and Preston, 1997; Yang et al., 2010). Income, driver licence, household type, and mode of transport also have influence on the distance traveled by the individuals (Mercado and Páez, 2009; Morency et al., 2011; Sultana, 2005). The following variables were found to have statistically significant spatial expansion components: age, age squared, gender (female), and income levels. The spatial expansions were initially defined using quadratic trend surfaces complemented with distance to the Central Business District (CBD), although not all elements of the trend were significant for every single spatially-expanded variable. Non-significant variables were excluded in a step-wise search procedure that followed a general-to-specific strategy, beginning with an exhaustive model. All coefficients in the model are significant at least at the 5% level.

The results of the regression model with spatially expanded coefficients appear in Table 1. A total of 283,615 individual trips were used in the estimation. The coefficient of determination R^2 is 0.39, a relatively high value for this kind of analysis. In general, the estimated values conform to prior expectations and previous findings reported in the literature, including the non-monotonic effect of income, shorter trips for non-motorized modes, and the positive effect of mobility tools (e.g. driver license).

5. Technology

5.1. Interface design

To facilitate the calculation of accessibility by the general public, a web-based user interface was designed (http://www.science.mcmaster.ca/cspa/access_score). Design of the interface was kept simple to increase its user-friendliness. Input requirements for calculating accessibility are also minimal.

The interface allows users to select seven inputs along with a desired address to calculate the number of opportunities available within the distance of a typical trip. The user inputs are as follows: age, gender, possession of driver licence, income level, main occupation, household type, and mode of travel. All inputs are categorical, with the exception of age, which is a continuous variable. Among the categorical responses, gender (male or female) and driver licence ownership (yes or no) are dichotomous, household income has six levels (less than 20 K, 20–40 K, 40–60 K, 60–80 K, 80–100 K, and more than 100 K), occupation has five classes (fulltime, part-time, student, retired, work at home), household type offers four alternatives (single, couple, couple with child, and single parent), and mode of transportation has four different options (walk, cycle, car as driver, and car as passenger). The interface was implemented using Google Maps API v3 and Javascript. The map shown on the web-page is retrieved from the Google server with a pre-defined center and extent.

In addition to the map and fields for typing/selecting inputs, the interface includes information about the design, and simple instructions for use. The documentation can be accessed using links provided. As well, there are links that redirect to the academic sites of the developers, and to email the lead author of the paper. The calculator is currently designed for individual use. However, there is also the possibility of conducting batch operations offline, by contacting the authors. The design of the interface is shown in Fig. 1.

5.2. Operation

In order to use the accessibility calculator, the user must enter an address of interest, and the seven profile-specific attributes. Once the user clicks on the button "SEE MY MAP", the script underlying the interface first reads the address entered by the user and forwards it as a geocoder request to the Google Maps API. Upon receiving the request, the Google Maps API looks up the address in its hardcoded address property. A couple of issues need to be resolved at this point. First, the address entered by the user may not match an exact hardcoded address. This requires the addition of a function to the geocoder request. The function is used to check the status of the geocoder request, which will be completed only if the Google Maps API can verify the status of the address. Secondly, an entered address may have a homonym at a different geographic location, which would result in an array being returned. At this point, we depend on the geocoder request to report the most relevant address in the first place. A simple solution is to provide a greater degree of specificity in the input. Once the request has been validated, the built-in functionality of the API allows us to retrieve the coordinates (latitude and longitude) of the selected address. In its current implementation, a maximum of 2500 geocoding requests can be made during a 24-h period from a single IP address (Svennerberg, 2010). A larger number of requests would require the payment of a fee, which is currently disallowed by the calculator.

After the geocode for the address is retrieved by the API, the map is centred and a marker is placed on the map to show the location. The script then proceeds to read all other user inputs. The coefficients of the regression model are hardcoded in the script. The inputs, along with the coordinates, are used to obtain an estimate of trip length for the specified personal profile and location which in turns provides the adaptive threshold needed to implement the relative accessibility indicator.

Table 1
Regression model with spatially expanded coefficients.

Variable	Estimate	p-Value
Constant	2.07544	0.0000
Age	−18.28581	0.0000
Age squared	22.03076	0.0000
Gender (female = 1)	0.47034	0.0000
Occupation		
Full-time	Reference	
Part-time	−0.24677	0.0000
Student	0.02235	0.0091
Retired	−0.33518	0.0000
At-home	−0.49736	0.0000
Other	−0.39801	0.0000
Income (CAD)		
<20 K	Reference	
20–40 K	0.35884	0.0083
40–60 K	0.33928	0.0020
60–80 K	0.60658	0.0001
80–100 K	0.46343	0.0000
>100 K	0.43943	0.0000
Do not know	0.12359	0.0000
Household type		
Single	Reference	
Couple	0.05113	0.0000
Couple W/children	−0.23032	0.0000
Single parent	−0.26449	0.0000
Driver licence	0.18461	0.0000
Mode of transport		
Car as driver	Reference	
Car as passenger	0.01844	0.0061
Transit	0.39636	0.0000
School bus	0.06512	0.0000
Walk	−1.80475	0.0000
Cycle	−0.68306	0.0000
Kiss and ride	1.10158	0.0000
Park and ride	1.08716	0.0000
Other mode	2.48917	0.0000
Trend surface (coordinates u and v)		
u Squared	0.015	0.0000
u	0.2305	0.0000
$v * u$	−0.00993	0.0000
v	−0.26708	0.0000
v squared	0.01783	0.0000
Spatial expansion: age		
Distance from CBD	2.41404	0.0000
$^{*}u$ squared	−0.21217	0.0000
$^{*}u$	−2.78028	0.0000
$^{*}v * u$	0.07315	0.0000
$^{*}v$	4.42945	0.0000
$^{*}v$ squared	−0.37484	0.0000
Spatial expansion: age squared		
*Distance from CBD	−2.95525	0.0000
$^{*}u$ squared	0.25433	0.0000
$^{*}u$	3.36622	0.0000
$^{*}v * u$	−0.09337	0.0000
$^{*}v$	−5.19517	0.0000
$^{*}v$ squared	0.43802	0.0000
Spatial expansion: female		
*Distance from CBD	−0.08453	0.0000
$^{*}u$ squared	0.00545	0.0000
$^{*}u$	0.0583	0.0000
$^{*}v$	−0.13024	0.0000
$^{*}v$ squared	0.01276	0.0000
Spatial expansion: income 20–40 K		
*Distance from CBD	−0.06829	0.0000
$^{*}u$ squared	0.00588	0.0000

(*continued on next page*)

Table 1 (*continued*)

Variable	Estimate	*p*-Value
$^{*}u$	0.06789	0.0002
$^{*}v$	−0.0681	0.0494
$^{*}v$ squared	0.00968	0.0057
Spatial expansion: income 40–60 K		
*Distance from CBD	−0.03666	0.0000
$^{*}u$	−0.02457	0.0024
$^{*}v * u$	0.0023	0.0574
$^{*}v$	−0.11542	0.0012
$^{*}v$ squared	0.01128	0.0003
Spatial expansion: income 60–80 K		
*Distance from CBD	−0.02427	0.0432
$^{*}u$ squared	0.00476	0.0017
$^{*}u$	0.07524	0.0002
$^{*}v * u$	−0.00255	0.0565
$^{*}v$	−0.0992	0.0128
$^{*}v$ squared	0.00832	0.0206
Spatial expansion: income 80–100 K		
$^{*}v$	−0.06055	0.0000
$^{*}u$	0.05571	0.0000
$^{*}v * u$	−0.01042	0.0000
Spatial expansion: income > 100 K		
*Distance from CBD	0.02488	0.0089
$^{*}u$ Squared	0.006	0.0001
$^{*}u$	0.08353	0.0000
$^{*}v$ Squared	−0.00091	0.0625

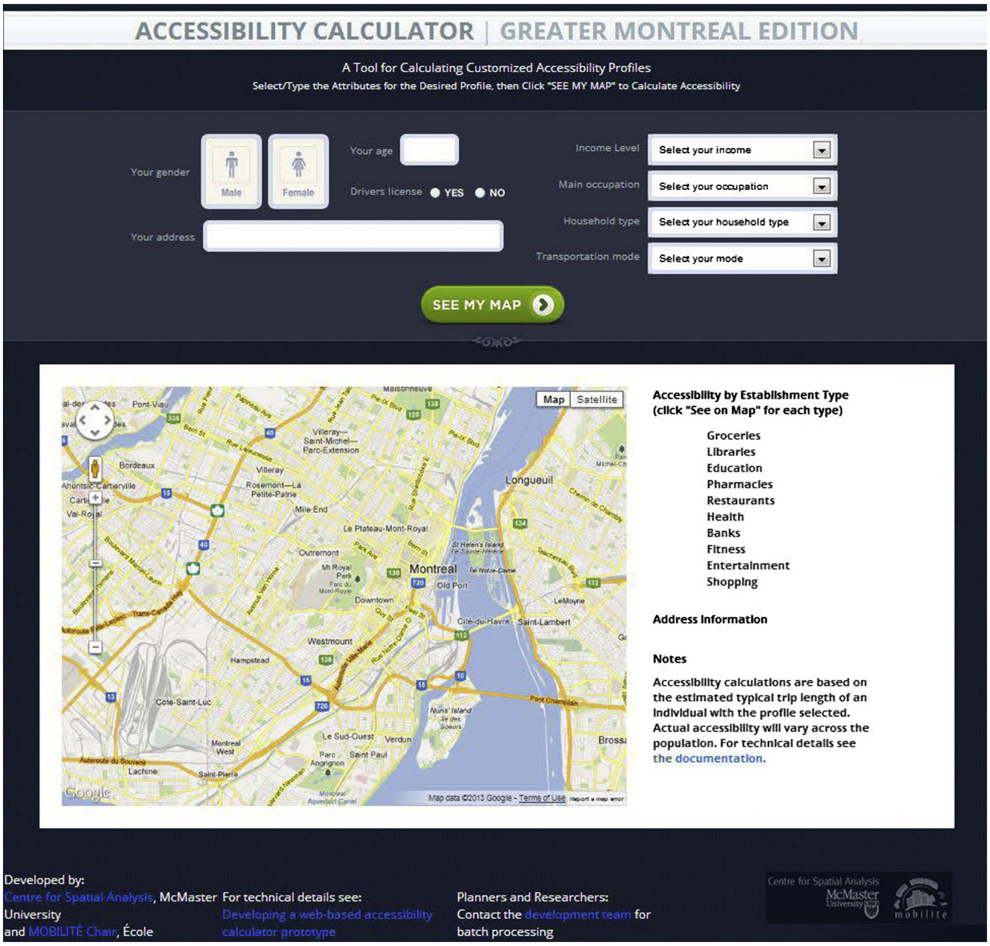

Fig. 1. User interface of the web-based accessibility calculator.

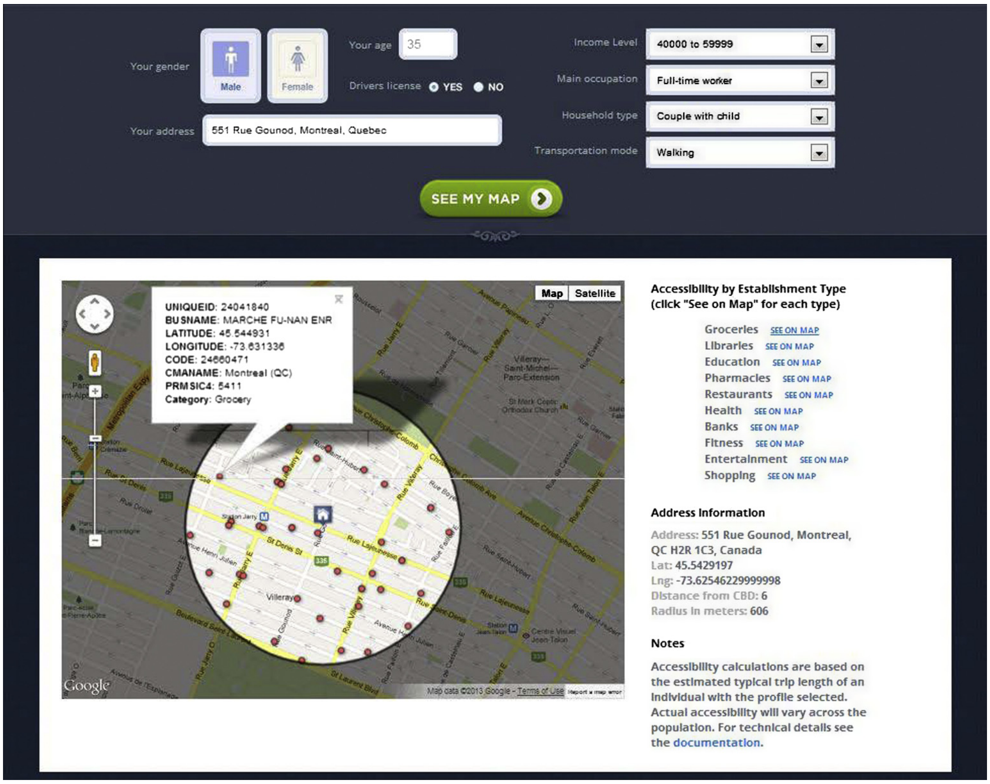

Fig. 2. Basic functionality of the accessibility calculator.

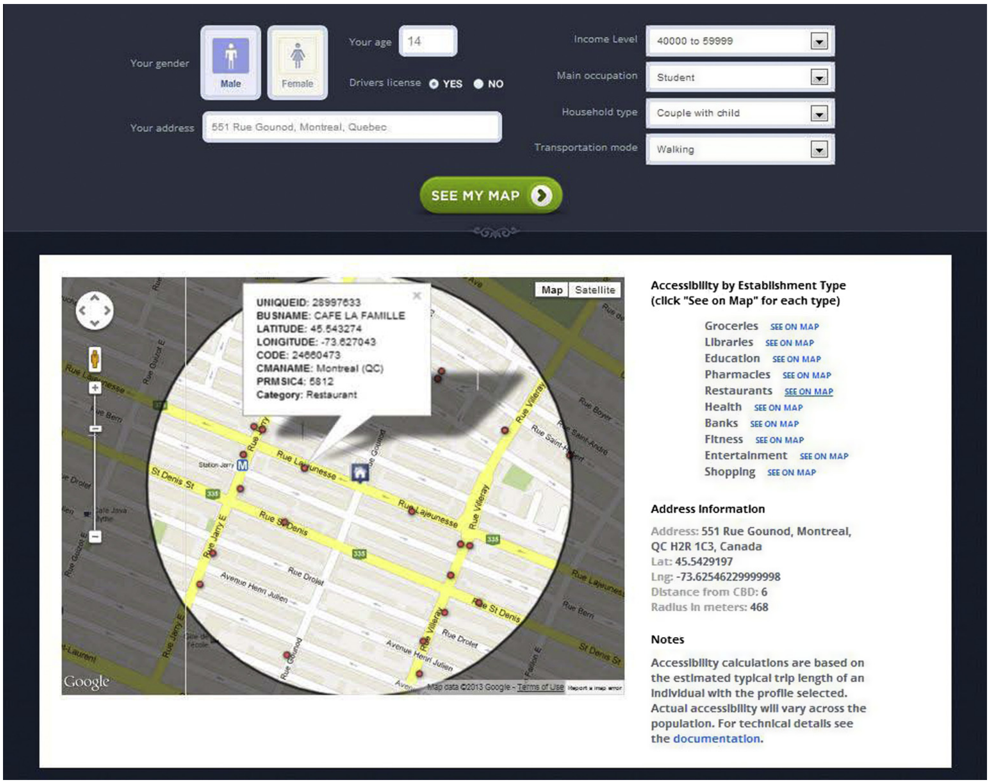

Fig. 3. Accessibility of a younger traveler.

The second element of the accessibility indicator is the opportunity landscape. Once the adaptive threshold has been calculated, the script performs a geographical query of the business database, selecting all business located at a distance equal to or less than the estimated trip length. The script then displays the estimated range for the selected profile and location by means of a circle with radius equal to the adaptive threshold. As well, the business locations of each type are reported in the web-page and can further be pinpointed in the map for convenience.

6. Illustration

In this section of the paper, we illustrate different possible uses of the accessibility calculator. A key feature of the calculator is its ability (based on the use of the spatial modeling approach) to capture between-person and between-place variations in the estimates of accessibility. Therefore, in addition to demonstrating the basic functionality of the calculator, we illustrate this feature using scenarios that compare identical geography but different individual profiles, and identical individual profiles but different geographies.

6.1. Basic functionality

The basic functionality of the accessibility calculator provides users with the ability to explore their neighborhoods, for instance to locate opportunities of interest within the range of a typical trip by a designated mode. Consider for instance an individual, male, aged 35, employed full time with income in the 40,000–59,999 range, in possession of a driver license and living with a couple and children. As shown in Fig. 2, a typical walking trip for the indicated profile at a location on Rue Gounod, north of the downtown area grants access to 51 grocery stores, 5 schools, 5 pharmacies, 52 restaurants, 42 health care locales, 3 banks, 16 entertainment, and 46 shopping opportunities. The map can be panned and zoomed using familiar controls. In order to avoid overcrowding of points in the map, only a select set of locations is displayed using the control "SEE ON MAP". The figure shows businesses of the type "Grocery". The points can be queried by clicking on them, which prompts a dialog balloon to appear with additional information about the site.

6.2. Same geography, different individual profile

Suppose now that the same individual in the previous example is the father of a 14 year old boy, and is interested in assessing the child's walking accessibility at their place of residence. The profile now is for a male, aged 14, who is a student,

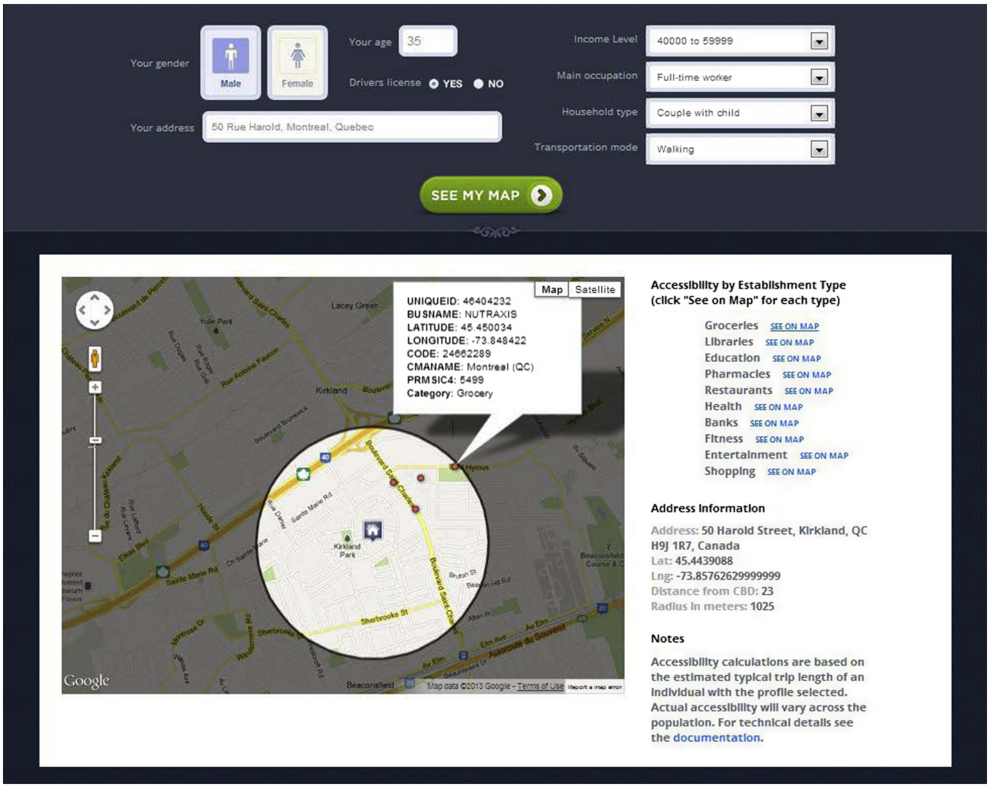

Fig. 4. Accessibility at a different location.

and does not have a driver license. Income level and family structure remain the same. As seen in Fig. 3, the typical trip length corresponding to the profile of this younger traveler is 389 m. Other things being equal, a lower threshold is associated with lower accessibility. The total number of opportunities reachable within a typical walking trip for this personal profile has decreased. The child has access to 26 grocery stores, 2 schools, 3 pharmacies, 28 restaurants, 31 health care locales, 3 banks, 8 entertainment opportunities, and 20 shopping opportunities. Note also that whereas the typical trip length for the profile of the father was sufficient to reach green spaces, this is not the case for the younger male.

6.3. Same individual profile, different geography

Another possible use of the accessibility calculator is to assess the potential of an address to support a lifestyle that involves walking. Consider the same personal profile as in the initial example (35-year old male). This individual is interested in perhaps moving to an address on Rue Harold, in a suburban location in eastern Montreal. As seen in Fig. 4, the typical walking trip there, at 1025 m, is longer than was the case at Rue Gounod for the same individual profile. However, even with this longer reach, accessibility is considerably lower. Relocating to this site would likely result in lower access and more limited choices for most opportunity types, including (shown in the map) grocery stores (5 versus 51), education (2 versus 5), pharmacies (2 versus 5), restaurants (15 versus 52), health care (26 versus 43), entertainment (8 versus 16), and shopping (13 versus 46). On the other hand, one library is within reach at this location.

The length of the typical trip would be associated with longer walks. Health benefits might result from this if the individual engaged in walking – however, the lower level accessibility and the need to cover longer distances to find fewer opportunities may discourage a potential walker. Overall, this location appears to be less well-suited for a lifestyle that involves walking.

7. Concluding remarks

In this paper we reported the development of a web-based accessibility calculator prototype for the Greater Montreal Area. The calculator implements the relative accessibility indicators introduced by Páez et al. (2010b), and provides an intuitive and user friendly web application for assessing accessibility by different forms of travel in the region. A key feature of the calculator is its ability to customize estimation of accessibility levels based on a suite of socio-economic and demographic attributes of the traveler. Further, the interface with Google Maps provides a powerful way to retrieve geographical information and perform the queries needed to calculate the accessibility indicator, while providing familiar tools for visualizing information and manipulating maps.

The accessibility calculator can be used in different ways, some of which were illustrated in the paper. Besides basic functionality to explore opportunities available at a given location, the calculator can be used to compare the effect on accessibility of life transitions (for instance, aging, having children, driving cessation), or to assess the potential of different residential locations to support lifestyles that involve walking. The experimental work of Rodriguez et al. (2011) suggests that providing information can encourage individuals to make more sustainable residential choices. Complementary anecdotal evidence suggests that many house buyers now routinely check WalkScore to assess the walkability of properties in neighborhoods. Likewise, providing information about destinations may help travelers to make more healthy travel choices.

As a prototype, future efforts can help to improve the accessibility calculator in a number of different ways.

First, the model of trip length is based on Euclidian distance, and could be modified in future versions of the calculator to network distance, to generate more realistic depictions of accessibility (Frank et al., 2005). The modelling required to do so is relatively straightforward, but implementation would require substantial additional work with the interface and the underlying layers of network information, as well as the calculation of shortest paths on networks (Su et al., 2010). Other modes of transportation could also be added as part of the menu. Currently only car (driver and passenger), walking, and cycling are implemented. These modes offer the most flexibility in terms of route selection, and thus are less sensitive to network constraints. Public transportation would be an important addition to the set of alternative modes, however, implementation becomes complicated by the fixity of routes and the points of entry into the system (e.g. transit stops and stations).

Secondly, accessibility is calculated based on the trip length estimated for a profile and location. There are likely places where people use certain modes more frequently than others. Therefore, another enhancement would be to implement a model of mode choice to provide additional information on the probability of a user using a certain mode. An example of such a model appears in Moniruzzaman et al. (2013).

Finally, in addition to interested members of the public, planners and/or researchers may find the profile-based outputs useful. For instance, planners interested in equity and fairness, may use the customized results to evaluate the delivery of various services to different demographic groups, or to plan land uses more sustainably for a wider range of individuals. Although the calculator is straightforward to use for a limited number of queries, online batch processing of large number of addresses and/or profiles is not currently supported. For interested parties we provide instead a link to contact the development team for inquiries regarding offline batch processing.

Acknowledgments

The authors wish to thank Heather McKay, Karim Khan, Vicky Scott, Ryan Rhodes, Maureen Ashe, Joanie Sims-Gould, Sarah Furst, and the members of the Walk the Talk Team (funded by a Canadian Institutes of Health Research Emerging Team) for valuable discussions at the conceptual stage of this research. The research was partially supported by SSHRC and NSERC grants to Antonio Páez.

References

Apparicio, P., Abdelmajid, M., Riva, M., Shearmur, R., 2008. Comparing alternative approaches to measuring the geographical accessibility of urban health services: distance types and aggregation-error issues. International Journal of Health Geographics, 7.

Bhat, C.R., Sen, S., Eluru, N., 2009. The impact of demographics, built environment attributes, vehicle characteristics, and gasoline prices on household vehicle holdings and use. Transportation Research Part B – Methodological 43, 1–18.

Brantingham, P.J., Brantingham, P.L., 2008. Crime Pattern Theory. In Environmental Criminology and Crime Analysis. Willan Publishing, Portland, OR.

Buliung, R., Sultana, S., Faulkner, G., 2012. Guest editorial: special section on child and youth mobility – current research and nascent themes. Journal of Transport Geography 20, 31–33.

Byrne, M., 2011. The role of transport information in influencing travel behaviour: a literature review. Road and Transport Research 20, 40–49.

Casas, I., 2007. Social exclusion and the disabled: an accessibility approach. Professional Geographer 59, 463–477.

Casetti, E., 1972. Generating models by the expansion method: applications to geographic research. Geographical Analysis 4, 81–91.

Cervero, R., 1988. Land-use mixing and suburban mobility. Transportation Quarterly 42, 429–446.

Cervero, R., 2002a. Built environments and mode choice: toward a normative framework. Transportation Research Part D – Transport and Environment 7, 265–284.

Cervero, R., 2002b. Travel by design: the influence of urban form on travel. Journal of the American Planning Association 68, 106–107.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transportation Research Part D – Transport and Environment 2, 199–219.

Cherry, C., Hickman, M., Garg, A., 2006. Design of a map based transit itinerary planner. Journal of Public Transportation 9, 45–68.

Clarke, G., Eyre, H., Guy, C., 2002. Deriving indicators of access to food retail provision in British cities: studies of cardiff, leeds and bradford. Urban Studies 39, 2041–2060.

Currie, G., Gook, M., 2009. Measuring the performance of transit passenger information websites. Transportation Research Record, 137–148.

Dobbs, L., 2005. Wedded to the car: women, employment and the importance of private transport. Transport Policy 12, 266–278.

Ewing, R., Handy, S., 2009. Measuring the unmeasurable: urban design qualities related to walkability. Journal of Urban Design 14, 65–84.

Farber, S., Páez, A., Morency, C., 2011. Activity Spaces and the Measurement of Clustering and Exposure: A Case Study of Linguistic Groups in Montreal. Environment and Planning Part A (forthcoming).

Frank, L., Engelke, P., Schmid, T., 2003. Health and Community Design: The Impact of The Built Environment on Physical Activity. Island Press, Washington, DC.

Frank, L.D., Andresen, M.A., Schmid, T.L., 2004. Obesity relationships with community design, physical activity, and time spent in cars. American Journal of Preventive Medicine 27, 87–96.

Frank, L.D., Schmid, T.L., Sallis, J.F., Chapman, J., Saelens, B.E., 2005. Linking objectively measured physical activity with objectively measured urban form – findings from SMARTRAQ. American Journal of Preventive Medicine 28, 117–125.

Frank, L.D., Sallis, J.F., Saelens, B.E., Leary, L., Cain, K., Conway, T.L., Hess, P.M., 2010. The development of a walkability index: application to the Neighborhood Quality of Life Study. British Journal of Sports Medicine 44, 924–933.

French, R.L., 2006. Maps on wheels: the evolution of intelligent automobile navigation. In: Akerman, J.R. (Ed.), Cartographies of Travel and Navigation. University of Chicago Press, Chicago-London, pp. 260–290.

Glaeser, E.L., 2012. The challenge of urban policy. Journal of Policy Analysis and Management 31, 111–122.

Gliebe, J.P., Koppelman, F.S., 2002. A model of joint activity participation between household members. Transportation 29, 49–72.

Kuhnimhof, T., Armoogum, J., Buehler, R., Dargay, J., Denstadli, J.M., Yamamoto, T., 2012a. Men shape a downward trend in car use among young adults-evidence from six industrialized countries. Transport Reviews 32, 761–779.

Kuhnimhof, T., Buehler, R., Wirtz, M., Kalinowska, D., 2012b. Travel trends among young adults in Germany: increasing multimodality and declining car use for men. Journal of Transport Geography 24, 443–450.

Kuzmyak, R.J., Baber, C., Savory, D., 2005. Use of walk opportunities index to quantify local accessibility. Transportation Research Record, 145–153.

Kwan, M.P., 1999. Gender, the home-work link, and space-time patterns of nonemployment activities. Economic Geography 75, 370–394.

Lachapelle, U., Frank, L., Saelens, B.E., Sallis, J.F., Conway, T.L., 2011. Commuting by public transit and physical activity: where you live, where you work, and how you get there. Journal of Physical Activity and Health 8, S72–S82.

McLafferty, S., Preston, V., 1997. Gender, race, and the determinants of commuting: New York in 1990. Urban Geography 18, 192–212.

Mercado, R.G., Páez, A., 2009. Determinants of distance traveled with a focus on the elderly: a multilevel analysis in the Hamilton CMA, Canada. Journal of Transport Geography 17, 65–76.

Metz, D., 2012. Demographic determinants of daily travel demand. Transport Policy 21, 20–25.

Mokhtarian, P.L., 1988. An empirical-evaluation of the travel impacts of teleconferencing. Transportation Research Part A – Policy and Practice 22, 283–289.

Mokhtarian, P.L., 1991. Telecommunications and travel behavior. Transportation 18, 287–289.

Mokhtarian, P.L., Chen, C., 2004. TTB or not TTB, that is the question: a review and analysis of the empirical literature on travel time (and money) budgets. Transportation Research Part A – Policy and Practice 38, 643–675.

Mokhtarian, P.L., Salomon, I., Handy, S.L., 2006. The impacts of ict on leisure activities and travel: a conceptual exploration. Transportation 33, 263–289.

Moniruzzaman, M., Paez, A., 2012. A model-based approach to select case sites for walkability audits. Health and Place 18, 1323–1334.

Moniruzzaman, M., Paez, A., Morency, C., 2013. Mode use and trip length of seniors in Montreal. Journal of Transport Geography 30, 89–99.

Morency, C., Páez, A., Roorda, M.J., Mercado, R.G., Farber, S., 2011. Distance traveled in three Canadian cities: spatial analysis from the perspective of vulnerable population segments. Journal of Transport Geography 19, 39–50.

Moudon, A.V., Lee, C., Cheadle, A.D., Garvin, C., Johnson, D., Schmid, T.L., Weathers, R.D., Lin, L., 2006. Operational definitions of walkable neighborhood: theoretical and empirical insights. Journal of Physical Activity and Health 3, S99–S117.

Newman, P., Matan, A., 2012. Human mobility and human health. Current Opinion in Environmental Sustainability 4, 420–426.

O'Kelly, M.E., Horner, M.W., 2003. Aggregate accessibility to population at the county level: U.S. 1940–2000. Journal of Geographical Systems 5, 5–23.

Páez, A., Mercado, R., Farber, S., Morency, C., Roorda, M., 2010a. Accessibility to health care facilities in Montreal Island: an application of relative accessibility indicators from the perspective of senior and non-senior residents. International Journal of Health Geographics 9, 1–9.

Páez, A., Mercado, R.G., Farber, S., Morency, C., Roorda, M., 2010b. Relative accessibility deprivation indicators for urban settings: definitions and application to food deserts in montreal. Urban Studies 47, 1415–1438.

Paez, A., Scott, D.M., Morency, C., 2012. Measuring accessibility: positive and normative implementations of various accessibility indicators. Journal of Transport Geography 25, 141–153.

Paez, A., Farber, S., Mercado, R., Roorda, M., Morency, C., 2013. Jobs and the single-parent: an analysis of accessibility to employment in Toronto. Urban Geography 34, 815–842.
Parmenter, B., McMillan, T., Cubbin, C., Lee, R.E., 2008. Developing geospatial data management, recruitment, and analysis techniques for physical activity research. Journal of the Urban and Regional Information Systems Association 20, 13–19.
Rabl, A., de Nazelle, A., 2012. Benefits of shift from car to active transport. Transport Policy 19, 121–131.
Rodriguez, D.A., Joo, J., 2004. The relationship between non-motorized mode choice and the local physical environment. Transportation Research Part D – Transport and Environment 9, 151–173.
Rodriguez, D.A., Levine, J., Agrawal, A.W., Song, J.M., 2011. Can information promote transportation-friendly location decisions? A simulation experiment. Journal of Transport Geography 19, 304–312.
Roorda, M.J., Paez, A., Morency, C., Mercado, R., Farber, S., 2010. Trip generation of vulnerable populations in three Canadian cities: a spatial ordered probit approach. Transportation 37, 525–548.
Sallis, J.F., Bauman, A., Pratt, M., 1998. Environmental and policy – interventions to promote physical activity. American Journal of Preventive Medicine 15, 379–397.
Sallis, J.F., Bowles, H.R., Bauman, A., Ainsworth, B.E., Bull, F.C., Craig, C.L., Sjostrom, M., De Bourdeaudhuij, I., Lefevre, J., Matsudo, V., Matsudo, S., Macfarlane, D.J., Gomez, L.F., Inoue, S., Murase, N., Volbekiene, V., McLean, G., Carr, H., Heggebo, L.K., Tomten, H., Bergman, P., 2009. Neighborhood environments and physical activity among adults in 11 countries. American Journal of Preventive Medicine 36, 484–490.
Schmocker, J.D., Quddus, M.A., Noland, R.B., Bell, M.G.H., 2005. Estimating trip generation of elderly and disabled people – analysis of London data. Transportation Research Record, 9–18.
Schwanen, T., Páez, A., 2010. The mobility of older people – an introduction. Journal of Transport Geography 18, 591–595.
Scott, D.M., Horner, M.W., 2008. Examining the role of urban form in shaping people's accessibility to opportunities: an exploratory spatial data analysis. Journal of Transport and Land Use 1, 89–119.
Scott, D.M., Kanaroglou, P.S., 2002. An activity-episode generation model that captures interactions between household heads: development and empirical analysis. Transportation Research Part B – Methodological 36, 875–896.
Skog, I., Handel, P., 2009. In-car positioning and navigation technologies – a survey. Ieee Transactions on Intelligent Transportation Systems 10, 4–21.
Su, J.G., Winters, M., Nunes, M., Brauer, M., 2010. Designing a route planner to facilitate and promote cycling in Metro Vancouver, Canada. Transportation Research Part A – Policy and Practice 44, 495–505.
Sultana, S., 2005. Effects of married-couple dual-earner households on metropolitan commuting: evidence from the atlanta metropolitan area. Urban Geography 26, 328–352.
Svennerberg, G., 2010. Beginning Google Maps API 3. Apress Publisher, New York.
Turner, T., Niemeier, D., 1997. Travel to work and household responsibility: new evidence. Transportation 24, 397–419.
Urban Transportation Task Force, 2012. The High Cost of Congestion in Canadian Cities. Council of Ministers Responsible for Transportation and Highway Safety, <http://www.comt.ca/english/uttf-congestion-2012.pdf>.
Wang, D.G., Law, F.Y.T., 2007. Impacts of Information and Communication Technologies (ICT) on time use and travel behavior: a structural equations analysis. Transportation 34, 513–527.
Watkins, K.E., Ferris, B., Rutherford, G.S., 2010. Explore: an attraction search tool for transit trip planning. Journal of Public Transportation 13, 111–128.
Yang, M., Wang, W., Chen, X., Wang, W., Xu, R., Gu, T., 2010. Modeling destination choice behaviour incorporating spatial factors, individual socio-demographics, and travel mode. Journal of Transportation Engineering 136, 800–810.