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Hartwig H. Hochmair
University of Floida

Eli Brossell
University of Florida

Zhaohui J. Fu
Florida International University, Fujen@fiu.edu

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Corresponding Author:
hhhochmair@ufl.edu
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Identification of Transit Service Gaps through Accessibility and Social Vulnerability Mapping in Miami-Dade County

Hartwig H. Hochmair[1], Eli Brossell[1] and Zhaohui J. Fu[2]
[1]University of Florida, USA
[2]Florida International University, USA

Abstract

Inadequate provision of public transportation services can lead to mobility-related social exclusion for disadvantaged population groups (e.g., lower-income families, the elderly), and limited accessibility to jobs, healthy food, and recreational as well as social activities. The aim of this study is to identify areas in Miami-Dade County, Florida, where disadvantaged populations lack transit-based access to these opportunities, and where transit service improvement could benefit these groups especially. This involves developing a transit-based accessibility index which uses timetable data from three public transit agencies. It also entails devising a vulnerability index based on a combination of socioeconomic variables to identify disadvantaged population groups with regards to mobility. Both indices can be combined into a service provision score which quantifies the presence of populations in need of transit service improvements. Results show that the combination of the different index maps and the application of Hotspot analysis can help to identify areas requiring transit service improvement in order to achieve accessibility equity. The analysis and interpretation of accessibility maps and selected demographic layers, such as percentage of households without vehicle, facilitates the identification of areas with above-average rates of users who rely on public transportation.

Keywords:

multi-modal network, transit equity, GTFS, accessibility

1 Introduction

Accessibility and mobility are interrelated concepts which play a major role in our everyday lives. Mobility measures the ability to move from one location to another (Hansen, 1959); it relates to the physical movement of goods or people, measured by trips, speed, distance or tonnage. Accessibility relies on mobility, and measures the 'ease' of reaching goods, services, activities and destinations as a function of available opportunities moderated by some measure of impedance, which is often denoted as travel distance or travel time (Niemeier, 1997). Destinations provide opportunities, which can be measured in terms, for example, of employment positions or retail or non-retail square footage (Handy & Niemeier, 1997). Access is the goal of most transportation activity, except where travel is undertaken for its own sake, as in the case of sight-seeing train rides. Transit accessibility indicators measure the role of landuse and transit infrastructure supply on an individual's opportunities to participate in activities at various locations through use of public transportation. Transit equity indicators assess the impact of landuse and transit infrastructure on populations with the greatest potential need for public transportation (Yeganeh, Hall, Pearce, & Hankey, 2018): elderly residents, people with disabilities, individuals in low-income households, and those living in rural areas can face significant mobility challenges (Luiu, Tight, & Burro, 2017; Mattson & Molina, 2022). Transportation equity and mobility justice pay attention to how public transportation access is distributed amongst captive (e.g., low-income) riders, and how public transport can contribute to the mitigation of social exclusion (Garrett & Taylor, 1999).

Mobility-related social exclusion is the process by which, due to an insufficiency or the non-existence of adequate means to travel, people are prevented from participating in the economic, political and social life of the community (Kenyon, Lyons, & Rafferty, 2002). These conditions are often reinforced by poverty and low levels of car ownership. Recent developments in open data initiatives make it possible to use desktop GIS software to compute transit accessibility using timetable information and to guide policy makers in reaching equitable transportation provision. For example, General Transit Feed Specification (GTFS) data from the Southwest Ohio Regional Transit Authority and the Transit Authority of Northern Kentucky have been used to analyse public transit access to supermarkets in Cincinnati, Ohio, at different times of day (Farber, Morang, & Widener, 2014), allowing the identification of disparities in accessibility to healthy food for various race, age and income groups.

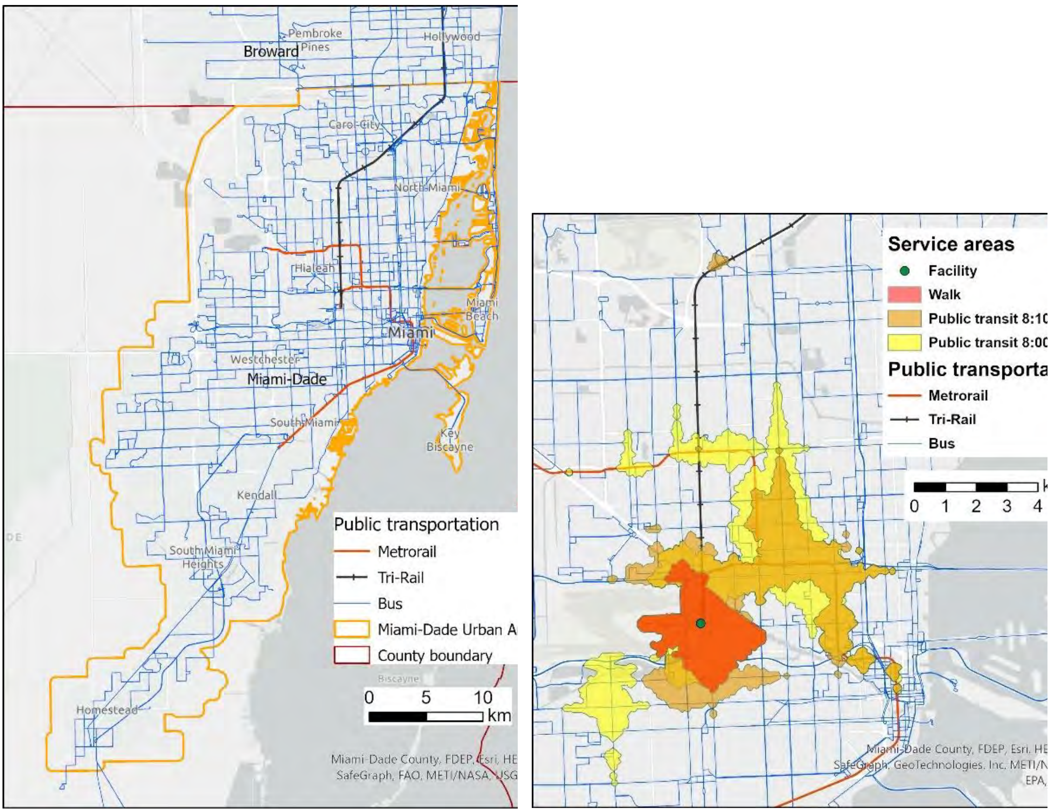
Transportation disadvantaged (TD) sociodemographic groups are prone to mobility-related social exclusion. To map areas with a high TD population, it is common to use some sort of social equity or vulnerability index, which is composed of socioeconomic variables. The development of a social vulnerability index involves multiple stages, such as the selection of demographic indicators, normalization of indicators, and summation to a final value (Tate, 2013). The City of Seattle, Washington, provides a Web mapping application that maps a composite index for racial and social equity at the census tract level (City of Seattle, 2020) to identify where priority populations make up relatively large proportions of neighbourhood residents. This index comprises several sub-indices – i.e., a race, English-language learners, and origins index, a health disadvantage index, and a socioeconomic disadvantage index. Each sub-index ranks census tracts by several weighted variables, for example persons of colour, foreign-born, income below 200% of poverty level, education below bachelor's degree, or disability. The City of Tacoma, Washington, maps an equity/opportunity index which highlights success and obstacles connected to upward mobility (City of Tacoma, 2021). The index consists of indicators within the city's strategic goals, i.e., accessibility, livability, education, economy and environmental health.

The remainder of this paper is structured as follows. The next section describes the study setup, including the study area, data sources, and the design of the multimodal network model used to compute service areas and generate accessibility maps. Section 3 introduces methods for building the different index maps. In Section 4, the maps are interpreted in the context of transportation planning and transportation equity. Section 5 provides closing remarks and presents directions for future work.

2 Study Setup

2.1 Study area

The study area comprises the Miami-Dade Urban Area within Miami-Dade County, Florida (Figure 1a). While the analysis of public transit service provision focuses on this area, the underlying transportation network as well as job and point of interest (POI) data used for computing accessibility scores need to be extended into adjacent Broward County for the computation of complete service areas and activity opportunities (jobs, supermarkets etc.). Miami-Dade Transit (MDT) operates a light rail system called Metrorail. It also operates over 90 bus routes in Miami-Dade County, including several express bus services. Broward County Transit (BCT) provides multiple express bus services and over 30 local bus routes in Broward County. Tri-Rail is a separate commuter rail system linking Miami-Dade, Broward and Palm Beach counties, and is managed by the South Florida Regional Transportation Authority (SFRTA). Timetables for public transportation operated by these three authorities can be used to compute service areas based on origin locations (see Figure 1b for service area examples).



a) b)

Figure 1: (a) Public transportation network in Miami-Dade County and part of adjacent Broward County; (b) 30-minute service areas for public transportation modes and walking away from a facility near Miami International Airport

2.2 Data sources for social vulnerability and accessibility scores

To identify areas with TD populations, a list of 11 socioeconomic variables was compiled (see Table 1) based on the related literature (Cebollada, 2009; Grengs, 2012; Kenyon et al., 2002). Socioeconomic data were extracted from American Community Survey (ACS) for a 5-year period (2014–2019) for census block groups intersecting with the Miami-Dade Urban Area (n = 1,600). After removal of 19 census block groups that have a household count of zero (e.g., airports), 1,581 were retained for further analysis.

Job and POI themes were chosen based on necessities of daily life, such as employment, health and food services, and opportunities for recreation and outdoor activities (Table 1). This list could be expanded to other types of opportunities, such as education, training or political participation (Cebollada, 2009). The job and POI counts are used as opportunities in the computation of accessibility indices.

Table 1: Variables related to social vulnerability and travel opportunities

Topic	Variable description	Data source
Sociodemographic		
Age	% population < 18 years % population > 65 years	US Census Bureau – American Community Survey (ACS) 5-year census block group data (2014-2019)
Race and ethnicity	% Black population % Hispanic population	
Origin	% Foreign-born population	
Income	% Households in poverty % Population (above 15 years) unemployed	
Education	% Population (above 24 years) without high school diploma	
Health	% Households with one or more persons with disability % Population (above 18 years) with Medicare insurance only	
Mobility	% Households without vehicle	
Opportunities		
Jobs	Number of jobs per census block	US Census Bureau – Longitudinal Employer–Household Dynamics 2019
Points of Interest	Location of post offices, supermarkets, parks and recreational areas, and hospitals	HERE NAVSTREETS Cultural Features (4th Quarter 2021)

2.3 Designing the multimodal network

Computing the accessibility of a location requires an underlying transportation network and involves identifying a route between two points, based on travel cost associated with traversing network edges or junctions. Finding routes forms the basis for the computation of service areas, which model the area that can be reached from a point of origin within a given time or distance. A multimodal network was built using ESRI's Network Analyst extension, which can incorporate public transit timetable information from GTFS data. The three agencies operating public transportation in Miami-Dade County and Broward County provided timetable data files for their services, which were used to build the multimodal network (Table 2).

HERE NAVSTREETS street data were used as the underlying road network in the multimodal network. For comparison of service areas and accessibility with other modes, car and pedestrian travel modes were also modelled in the network. For route segments completed on foot (e.g., to reach a public transit stop), a walking speed of 83.3 m/min is assumed along accessible roads. The street dataset contains access restrictions for pedestrians (e.g., along highways) and cars (e.g., on footpaths). These were integrated in the walk, public transit and car modes. The car mode uses travel speeds observed on Tuesdays at 8am (rush-hour) on roads of functional classes 1, 2, 3 and 4 (i.e., highways, arterial roads, and collector roads that link neighbourhoods) based on HERE Historical Travel Pattern data. For roads falling into functional class 5 (i.e., streets smaller than collector roads, such as local streets, access roads and parking lots), the typical travel speed, based on the road's speed category attribute, was used instead. The car travel mode takes into account one-way restrictions and waiting times of between 30 and 60 seconds at intersections with traffic signals (Table 2).

Table 2: Datasets used for the multimodal transportation network

Features	Area	Dataset	Data source
Road network	Miami-Dade, Broward	HERE NAVSTREETS street file: one-way restrictions, traffic signals, speed categories	FDOT's Unified Basemap Repository (1st Quarter 2020)
Road travel speeds	Miami-Dade, Broward	HERE Historical Travel Pattern: hourly road travel speeds	
Tri-Rail schedule	Miami-Dade, Broward	GTFS files	SFRTA (July 2021)[1]
Bus/Metrorail schedule	Miami-Dade	GTFS files	MDT (July 2021)[2]
Bus schedule	Broward	GTFS files	BCT (July 2021)[3]

[1] https://ftis.org/Posts.aspx?AspxAutoDetectCookieSupport=1

[2] https://transitfeeds.com/p/miami-dade-county-transit/48

[3] https://transitfeeds.com/p/broward-county-transit/49

Accessibility was computed using the Transit Network Analysis Tools (Morang, 2019) for locations on a 250 m x 250 m grid in the Miami-Dade Urban Area. These tools come as a Python toolbox which supplements the ArcGIS Network Analyst extension by accounting for the time-dependent nature of public transit. The 'Calculate Accessibility Matrix' tool facilitates accessibility calculations based on a set of origins and destinations, where the latter can be weighted based on a particular field, such as the number of jobs available. Since public transit routes and therefore accessibility counts can vary greatly by time of day, start and end times together with a time increment can be specified using the tool, so that multiple accessibility values can be obtained over the given time period. As an example, a comparison of yellow and orange service areas in Figure 1b illustrates how a shift in the departure time by just 10 minutes (i.e., from 8:00 am to 8:10 am) on a weekday affects the resulting service area. The figure also shows that the use of public transit significantly increases the service area compared to that of walk-only mode, and therefore improves access to opportunities. In this study, a time window on Wednesday between 8 am and 10 am with a 15-minute increment was chosen; separate accessibility maps were created for different sets of destinations (opportunity locations), including jobs, post offices, supermarkets, parks and recreational areas, and hospitals. The total number of opportunities reachable from an origin within 30 minutes at least once during the time window was then used as the accessibility value for that origin. The 30-minute threshold also includes the time needed to walk along the road network from a 250 m x 250 m cell centroid to a nearby transit stop, and from the transit egress point to the destination.

3 Analysis methods

3.1 Accessibility index

An accessibility index based on a gravity model is commonly used by transportation planners to assess the relative ease of reaching jobs or other opportunities in a metropolitan area. This modelling approach counts the number of opportunities reachable from a location or zone, adjusted for the relative difficulty of reaching the location. It can be formalized as follows (Hansen, 1959):

$A_i = \sum_{j=1}^{N} O_j \mathrm{f}(c_{ij})$ (eq. 1)

where

A_i	is the accessibility index at location *i*
O_j	is the number of opportunities at location *j*
$f(c_{ij})$	is the impedance or cost function to travel between locations *i* and *j*
N	is the number of locations or zones in the metropolitan region being analysed

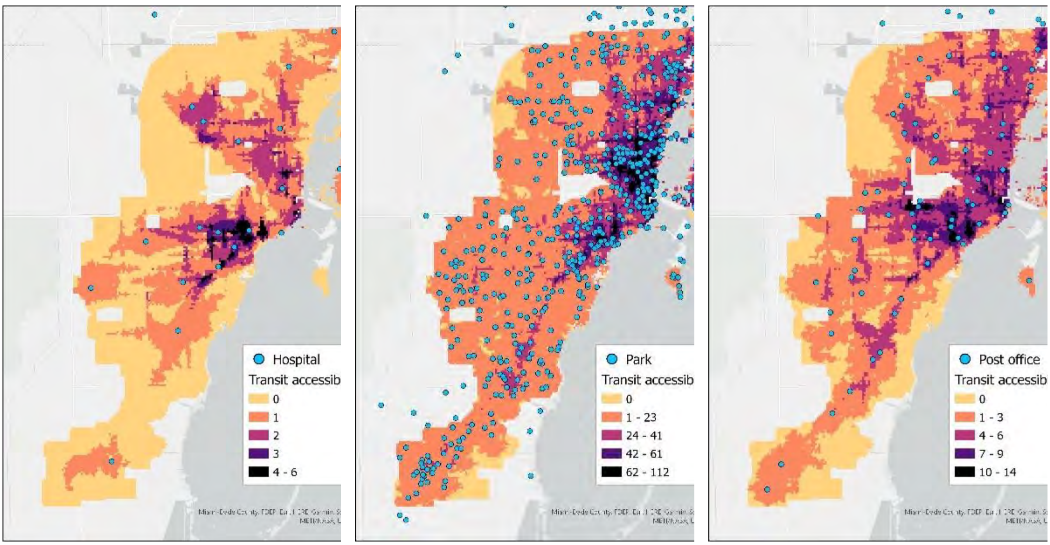
The impedance is often defined using a negative exponential function. The *isochronic* or *cumulative opportunity* measure is a special case of the gravity model; it counts the number of potential opportunities that can be reached within a predetermined travel time or distance, irrespective of the travel impedance. It can be formulated as follows (El-Geneidy & Levinson, 2008):

$A_i = \sum_{j=1}^{N} O_j b_j$ (eq. 2)

where b_i is the binary value, which equals 1 if location *j* is within the given distance or time threshold; otherwise, it is 0.

The Transit Network Analysis Tools derive the accessibility index based on the isochronic measure (eq. 2). To illustrate this, Figure 2 visualizes the accessibility to different types of opportunities (hospitals, parks, post offices, supermarkets, jobs) in the Miami-Dade Urban Area. The accessibility mapped reflects the number of opportunities that can be reached from a given cell within a 30-minute travel time budget using the specified travel mode. Figure 2a shows that large portions of the urban area lack access to hospitals by public transportation, whereas most locations do have access to parks (Figure 2b), post offices (Figure 2c), and supermarkets (Figure 2d). For transit accessibility to jobs (Figure 2e), accessibility values visually correlate with the spatial layout of the public transit network; for car accessibility (Figure 2f), a transit-independent spatial pattern is discernible. The fact that the number of jobs within reach of a given location is several times higher for car mode than for transit mode demonstrates the important role of car ownership as a gateway for access to a larger pool of jobs. This is especially relevant as a growing share of jobs are located at the suburban periphery (Grengs, 2012).

Z-scores (i.e. standardized values) for transport accessibility are obtained from z-scores of models using jobs and the four types of POIs as opportunities. That is, the final accessibility index used in this study is obtained by adding up the different z-scores for each grid cell. That sum is subsequently normalized to a range between 0 and 1 across the map.



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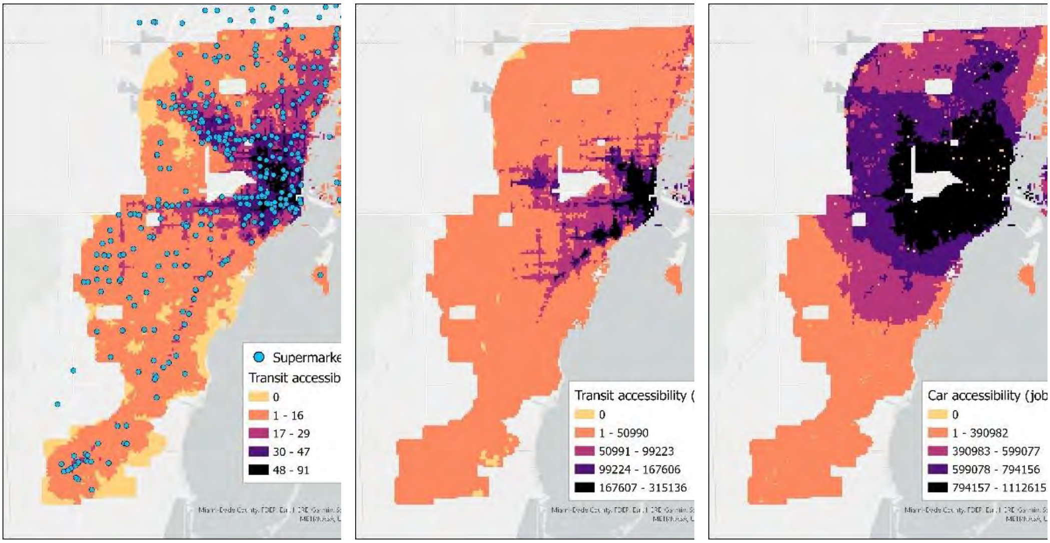


d) e) f)

Figure 2: Number of opportunities accessible using transit mode (a-e), and driving (f), based on a 30-minute travel budget

3.2 Vulnerability index

The vulnerability index for each census block group is computed by summing up the standardized values (z-scores) of the 11 socioeconomic variables selected, followed by normalization to a range between 0 and 1. Correlations between the 11 variables are moderate (Pearson's $r < 0.7$) (see Figure 3a).

Nevertheless, grouping socioeconomic variables into underlying (latent) variables, or selecting just a few variables which represent different characteristics of vulnerabilities can simplify the computation as well as the interpretation of vulnerability patterns. This study used Principal Components Analysis (PCA) for this purpose. PCA reduces the dimensionality of data by rotating the data to be best fitting with a set of perpendicular axes, or uncorrelated principal components (PCs). The rotations of these new axes relative to the original variables are called eigenvectors, and the variances along these axes are called eigenvalues. By performing a rotation, new axes might provide particular explanations that combine the semantics of several original data variables.

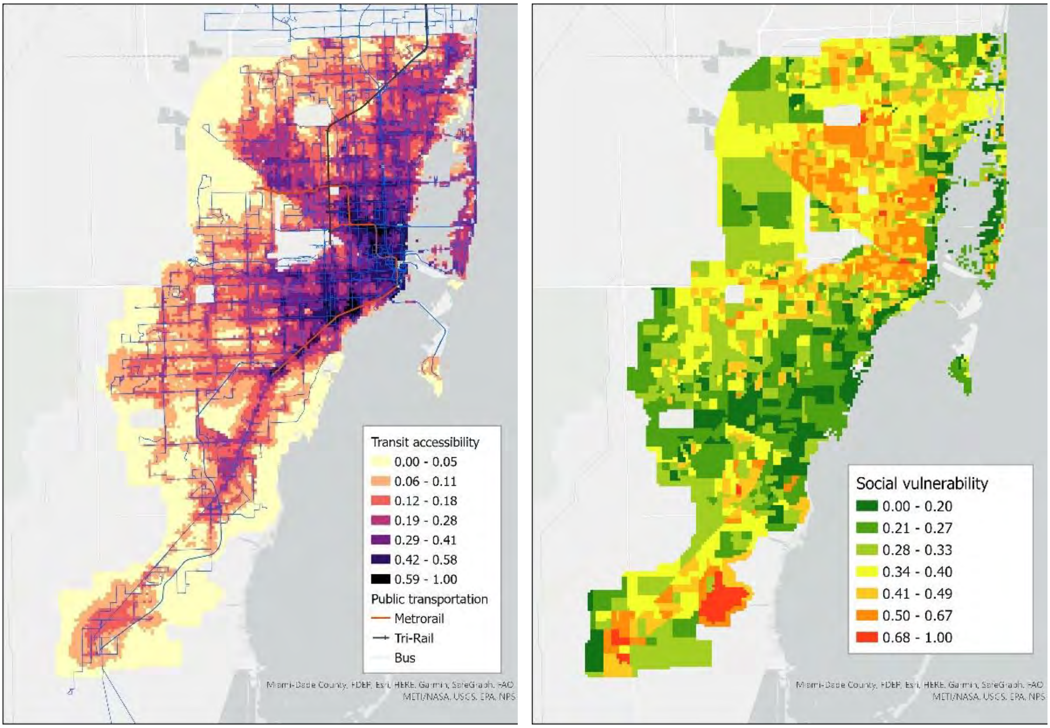
3.3 Service provision index

The service provision index considers both social vulnerability and accessibility. It is computed as the accessibility index value minus the vulnerability index value. For this operation, the vulnerability index needs to be re-sampled from census block group geometries to 250 m x 250 m grid cell locations. Statistically significant hotspots and coldspots of service provision can then be identified using Getis-Ord Gi* within the ArcGIS Pro Hot Spot Analysis tool.

4 Results

4.1 Mapping transit accessibility and social vulnerability

Figure 2a and 3b map transit accessibility and social vulnerability scores respectively. Areas with high transit accessibility scores feature a well-connected transportation network and access to many opportunities. Figure 2b shows that higher-income and established communities (e.g., along the beaches, historic homes to the south of Miami) are socially less vulnerable, whereas inland Miami Downtown and areas to the centre north and south of the county reveal higher social vulnerability.



a) b)

Figure 2: (a) Transit accessibility; (b) social vulnerability

4.2 Classification of social vulnerability

To explore natural clusters of social vulnerability variables, PCA is applied. For the task of PC selection, eigenvalues are commonly charted on a scree plot to visualize the decreasing rate at which variance is explained by additional PCs. A variety of criteria have been proposed to determine the number of PCs to examine (Abdi & Williams, 2010). One of them suggests keeping PCs up to the point of sudden change (the so-called 'elbow') in eigenvalues. Applied to our set of socioeconomic vulnerability variables (Figure 3b), four PCs, which account for about 72.3% of the explained variance, seems a reasonable number.

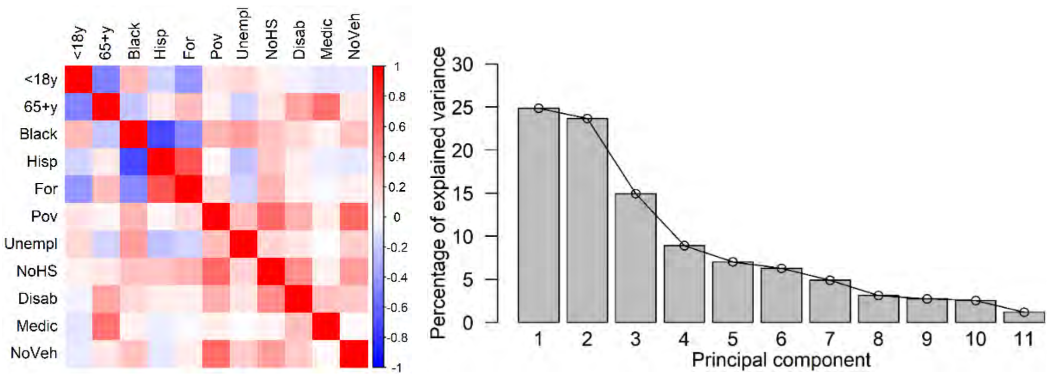


Figure 3: Analysis of correlation between 11 socioeconomic vulnerability variables: (a) correlation-coefficient matrix; (b) scree plot of eigenvalues for principal components

Table 3 shows the estimated correlations (called 'loadings') between the 11 original variables and the four components (i.e., latent variables). Large loadings (absolute value > 0.4) are highlighted in bold to emphasize variables that contribute strongly to a principal component.

Table 3: Rotated factor loadings for socioeconomic vulnerability variables

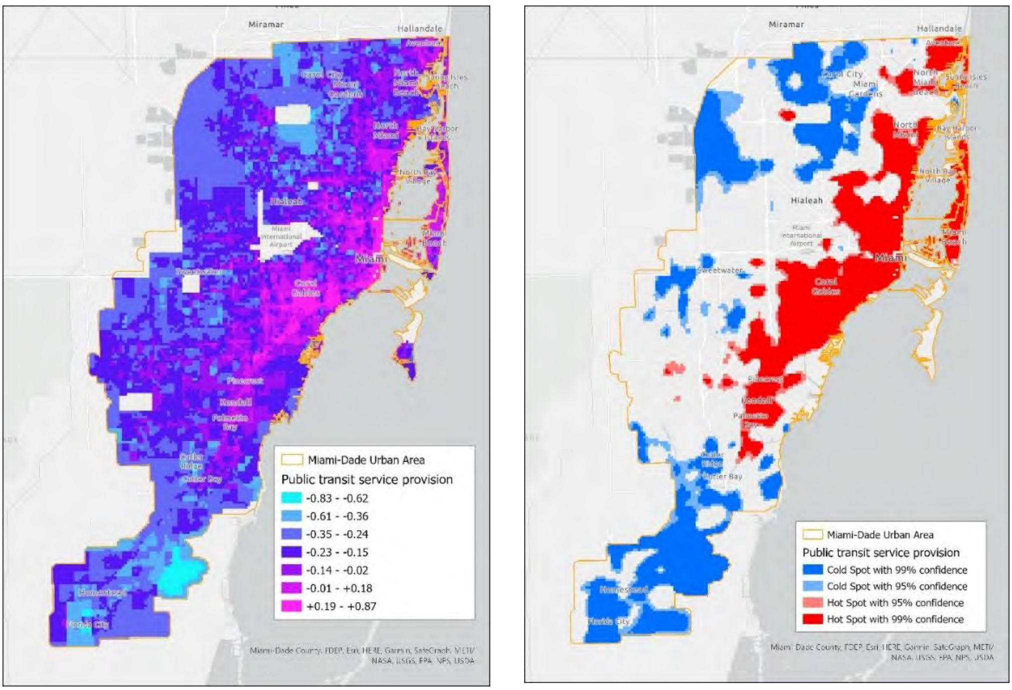
Variable	PC1	PC2	PC3	PC4
% Black population	**0.510**	0.120	-0.123	0.070
% Hispanic population	**-0.459**	0.113	0.359	-0.244
% Pop. foreign-born	**-0.433**	0.231	0.252	0.120
% Pop. (> 24 y.) without high school diploma	0.051	**0.485**	0.241	-0.222
% Households in poverty	0.164	**0.471**	0.213	0.062
% Pop. > 65 years	-0.272	0.269	**-0.520**	0.053
% Pop. (> 18 y.) with Medicare only	-0.057	0.198	**-0.559**	-0.278
% Pop. < 18 years	0.334	-0.114	0.242	**-0.624**
% Households without car	0.149	0.396	0.098	**0.456**
% Households with disability	0.015	**0.401**	-0.181	**-0.407**
% Pop. (> 15 years) unemployed	0.318	0.145	0.074	0.159

The loadings are readily interpretable. The first axis (PC1) reveals a positive loading for the percentage of the Black population, and negative loadings for the percentages of Hispanic and foreign-born populations (the latter two are positively correlated). This axis therefore highlights census blocks with a high percentage of African American inhabitants. These blocks are spatially distinct from areas with a primarily Hispanic population. Loadings on three variables on axis 2 show disadvantaged households in terms of education, income and disability. Axis 3 groups an older population with one that has only basic insurance (Medicare)

– a (combined) population that is vulnerable with regards to health and needs associated with aging. Axis 4 includes families without children under 18, and households without disabilities (negative loadings), hence variables associated with car independency. Results from **Table 3**, although not further examined in this paper, could be used to build a social vulnerability index that combines the different aspects (i.e. PCs) of social vulnerability by selecting one or two relevant variables from each PC (depending on the pattern of arithmetic signs (+/-) of loadings), summation of z-scores of the selected variables across PCs, and subsequent normalization.

4.3 Transit service gaps

Figure 4a maps service provision index values for 250 m x 250 m grid cells. Areas in magenta denote strong transit network connectivity or socially advantaged population groups, or both. As opposed to this, remote locations, especially those with TD population groups, appear in cyan. The corresponding hotspot map, which was constructed using a neighbourhood defined as having a 750-m fixed distance, is shown in Figure 4b. The False Discovery Rate correction (Benjamini & Hochberg, 1995) was applied. This accounted for multiple testing and spatial dependency respectively.



a) b)

Figure 4: (a) Transit service provision score, and (b) corresponding hotspot map

In order to quantify the differences in characteristics of areas that show adequate service provision versus those that do not, descriptive statistics of selected variables for census block groups whose centroid falls inside either a hotspot area (n = 573) or a coldspot area (n = 239) are compared in Table 4. The table lists means and standard errors of variables related to socioeconomic variables, travel opportunity and transit infrastructure. Numbers in bold indicate whether the hotspot or the coldspot area has the larger mean value. Except for two variables, all sociodemographic variables characterizing TD population groups are more pronounced in coldspot than in hotspot areas. Whereas mean values for the population aged 65 or older can be considered equivalent based on the similarity of mean values and the magnitude of the standard error, the percentage of households without vehicles is significantly higher for hotspot areas. This points towards users who opt not to own a car. Therefore, the lack of car ownership in these areas cannot necessarily be interpreted as an impediment to inclusion (Kenyon et al., 2002).

The second group in the table ('opportunities') shows that census block groups associated with hotspot areas generally have access to more opportunities, such as jobs. 'Transit network supply' contributes to high service provision. It can be measured by the number of stops (access points to the transit system) or by the total length of transit lines operating within a census block group.

Table 4: Mean and standard error (SE) of socioeconomic-, travel-opportunity- and transit-infrastructure-related variables for census block groups located in hotspot and coldspot areas

	Hotspot: Mean (± SE)	**Coldspot: Mean (± SE)**
Sociodemographic		
% population < 18 years	17.64 (0.37)	**23.43 (0.64)**
% population > 65 years	**17.05 (0.43)**	16.07 (0.59)
% Black population	16.14 (1.02)	**22.50 (1.73)**
% Hispanic population	58.06 (1.07)	**71.26 (1.66)**
% Foreign-born population	49.61 (0.74)	**50.97 (1.26)**
% Households in poverty	17.80 (0.59)	**22.77 (0.92)**
% Population (> 15 yrs) unemployed	3.47 (0.15)	**4.18 (0.23)**
% Population (> 24 yrs) without high school diploma	13.99 (0.53)	**26.21 (0.87)**
% Households with disability	18.65 (0.48)	**28.62 (0.77)**
% Population (> 18 yrs) with Medicare only	11.02 (0.28)	**13.22 (0.45)**
% Households without vehicle	**13.50 (0.59)**	8.83 (0.62)
Opportunities		
Jobs / sqkm	**2,743.35 (339.86)**	314.54 (34.18)
Post offices / sqkm	**0.20 (0.05)**	0.05 (0.01)
Supermarkets / sqkm	**0.74 (0.09)**	0.29 (0.06)

Parks / sqkm	**1.51 (0.14)**	0.49 (0.06)
Hospitals / sqkm	**0.01 (0.00)**	0.00 (0.00)
Transit network supply		
Public transit stops / sqkm	**17.72 (1.03)**	7.59 (0.42)
Bus or Metrorail lines (in km) / sqkm	**22.61 (1.25)**	7.55 (0.54)

For social equity with regards to transportation-related accessibility, an adequate public transportation service needs to be provided. This is especially true in areas with a large presence of TD population groups who lack access to other transportation modes, notably cars. These 'captive' mode users are individuals who have no other transportation option (Jacques, Manaugh, & El-Geneidy, 2013; Polzin, Chu, & Rey, 2000), because they do not have a driver's license or because they do not own a car. Reasons for mode captivity include age, disability, insufficient income, or other personal circumstances. 'Choice users', on the other hand, are those who have various options but select a certain mode because they view it as superior to other modes (Beimborn, Greenwald, & Jin, 2003).

Census block groups identified with black ellipses in Figure 5a are likely to have an above-average share of transit captive population, due to low car ownership rates and lower income (compare Figure 5b). These census block groups include parts of Miami Downtown and its extension north-west towards Miami Gardens and Opa-Locka, as well as some areas around Homestead. These areas also reveal low transit accessibility (compare Figure 2a), so they would specifically benefit from improved transit services. Areas with a potentially higher presence of transit-choice users tend to be those with (deliberately) low car ownership and higher incomes (blue ellipses in Figure 5a), as is the case in upcoming parts of the Miami Central Business District or areas near the beaches, e.g. Miami Beach and Surfside. In these densely populated areas, numerous opportunities can be reached by alternative transportation means (transit, walking, cycling). Elevated poverty rates in part of Miami's downtown (Figure 5b) combined with above-average transit accessibility (Figure 2a) for that area are indicative of how racial minorities and low-income households may in fact be advantaged in their ability to reach jobs, due to living in areas of better accessibility (Grengs, 2012).

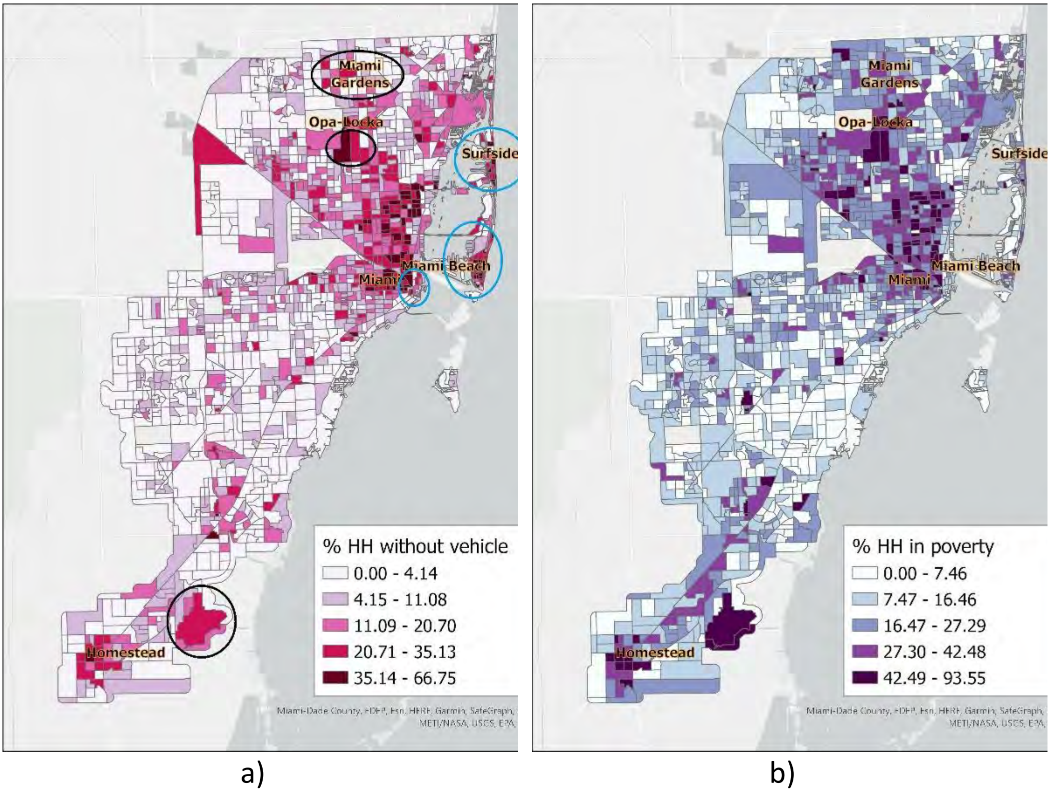


Figure 5: Exploring areas likely to have captive transit riders (black ellipses) and transit-choice riders (blue ellipses) through combining the census variables (a) percentage of households without vehicle and (b) percentage of households in poverty

5 Discussion and Conclusions

The study showcased the use of GTFS timetable information together with job and POI location data to identify areas in need of improved transit service provision, especially for TD population groups, in Miami-Dade County. The study setup can be replicated for different metropolitan areas inside or outside the U.S. and provide insights for transportation planners and policy makers for data-driven decision-making aimed at reducing social inequity in public transit. This study complements previous research. One study (Bejleri, Noh, Gu, Steiner, & Winter, 2018) identified gaps in public transit systems for TD populations by overlaying the TD population demand volume with transportation accessibility for Alachua County, Florida. In that study, accessibility to transportation services considered public transportation, on-demand services, and taxi services. Like our study, it found rural areas to be more prone to public transit service deficiency than areas closer to population centres. In addition, our approach also proposed the use of PCA for the reduction and grouping of vulnerability-related census attributes. A mixed-methods approach which combines quantitative and qualitative information to identify areas of potential transportation disadvantage was proposed in Shay et al. (2016). In that study, composite maps showing areas of elevated theoretical risk of transportation disadvantage (e.g., low-income households, ethnic minority households) based on census data were used as a starting point in interviews with local transportation-relevant professionals and meetings with non-expert residents. The study concludes that the mixed-methods approach may help practitioners address transportation disadvantage by identifying overlooked TD population groups and developing localized responses. For future work, comparison of accessibility indices for different modes of transportation (e.g., transit and car) could shed light on the spatial distribution of car-dependency and its role on the demographic composition and hence transportation equity in the study area.

Acknowledgements

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